eGo^N Data

Release 0.0.0

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CONTENTS

CHAPTER

ONE

ABOUT EGON-DATA

1.1 Project background

egon-data provides a transparent and reproducible open data-based data processing pipeline for generating data models suitable for energy system modeling. The data is customized for the requirements of the research project eGo_n. The research project aims to develop tools for open and cross-sectoral planning of transmission and distribution grids. For further information please visit the eGo_n project website. egon-data is a further development of the Data processing developed in the former research project open_eGo. It aims to extend the data models as well as improve the replicability and manageability of the data preparation and processing. The resulting data set serves as an input for the optimization tools eTraGo, ding0 and eDisGo and delivers, for example, data on grid topologies, demands/demand curves and generation capacities in a high spatial resolution. The outputs of egon-data are published under open-source and open-data licenses.

1.2 Objectives of the project

Driven by the expansion of renewable generation capacity and the progressing electrification of other energy sectors, the electrical grid increasingly faces new challenges: fluctuating supply of renewable energy and simultaneously a changing demand pattern caused by sector coupling. However, the integration of non-electric sectors such as gas, heat, and e-mobility enables more flexibility options. The eGo_n project aims to investigate the effects of sector coupling on the electrical grid and the benefits of new flexibility options. This requires the creation of a spatially and temporally highly resolved database for all sectors considered.

1.3 Project consortium and funding

The following universities and research institutes were involved in the creation of eGon-data:

- University of Applied Sciences Flensburg
- Reiner Lemoine Institut
- Otto von Guericke University Magdeburg
- DLR Institute of Networked Energy Systems
- Europa-Universität Flensburg

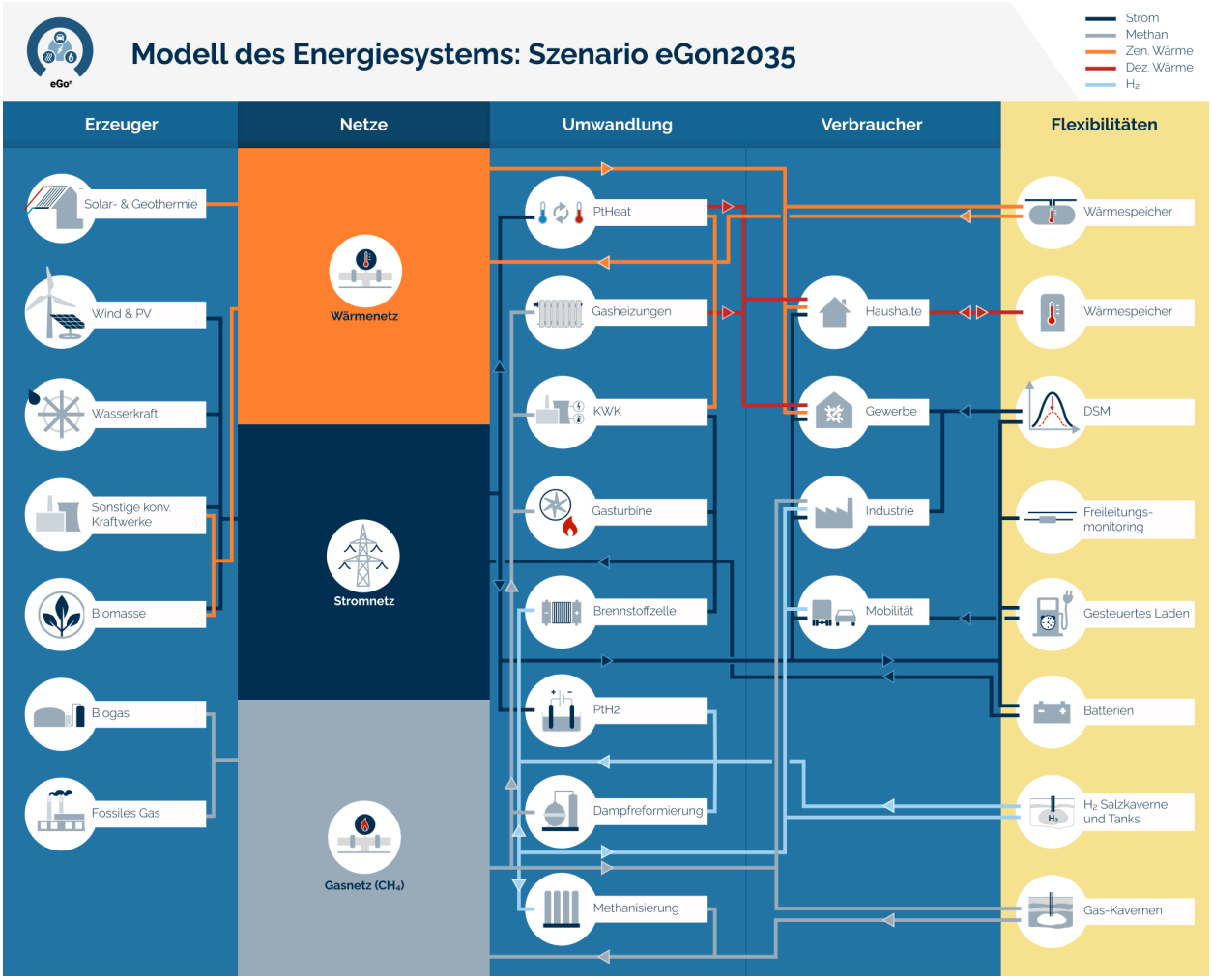
The eGo_n project (FKZ: 03EI1002) is supported by the Federal Ministry for Economic Affairs and Climate Action (BMWK) on the basis of a decision by the German Bundestag.

1.4 eGon-data as one element of the eGo-Toolchain

In the eGo_n project different tools were developed, which are in exchange with each other and have to serve the respective requirements on data scope, resolution, and format. The results of the data model creation have to be especially adapted to the requirements of the tools eTraGo and eDisGo for power grid optimization on different grid levels. A PostgreSQL database serves as an interface between the data model creation and the optimization tools. The figure below visualizes the interdependencies between the different tools.

1.5 Modeling concept and scenarios

eGon-data provides a data model suitable for calculations and optimizations with the tools eTraGo, eDisGo and eGo and therefore aims to satisfy all requirements regarding the scope and temporal as well as spatial granularity of the resulting data model. The following image visualizes the different components considered in scenario `eGon2035`.



eGon-data aims to create different scenarios, which differ in terms of RE penetration or the availability of flexibility options. Currently, the following scenarios are available or in progress.

- `eGon2035` Mid-termin scenario based on assumptions from the German network expansion plan 'scenario C2035', version 2021 and TYNDP
- `eGon2035_lowflex` Mid-termin scenario similar to 'eGon2035', but with a limited availability of flexibility options
- `eGon100RE` Long-term scenario with a 100% RE penetration, based on optimization results with PyPSA-Eur-Sec and additional data inputs (work-in-progress)

Table 1: Installed capacities of German power park in scenario `eGon2035` and `eGon2035_lowflex`

carrier	Installed capacities
gas	46.7 GW
oil	1.3 GW
pumped hydro	10.2 GW
wind onshore	90.9 GW
wind offshore	34.0 GW
solar	120.1 GW
biomass	8.7 GW
others	5.4 GW

Table 2: German energy demands in scenarios `eGon2035` and `eGon2035_lowflex`

Demand sector	Energy demand
MIT transport	41.4 TWh $_{el}$
central heat	68.9 TWh $_{th}$
rural heat	423.2 TWh $_{th}$
electricity	498.1 TWh $_{el}$
Methane industry	196.0 TWh $_{CH4}$
Hydrogen industry	16.1 TWh $_{H2}$
Hydrogen transport	26.5 TWh $_{H2}$

CHAPTER

TWO

WORKFLOW

2.1 Workflow management

2.2 Execution

In principle egon-data is not limited to the use of a specific programming language as the workflow integrates different scripts using Apache Airflow, but Python and SQL are widely used within the process. Apache Airflow organizes the order of execution of processing steps through so-called operators. In the default case the SQL processing is executed on a containerized local PostgreSQL database using Docker. For further information on Docker and its installation please refer to their documentation. Connection information of our local Docker database are defined in the corresponding docker-compose.yml

The egon-data workflow is composed of four different sections: database setup, data import, data processing and data export to the OpenEnergy Platform. Each section consists of different tasks, which are managed by Apache Airflow and correspond with the local database. Only final datasets which function as an input for the optimization tools or selected interim results are uploaded to the Open Energy Platform. The data processing in egon-data needs to be performed locally as calculations on the Open Energy Platform are prohibited. More information on how to run the workflow can be found in the getting started section of our documentation.

2.3 Versioning

Warning: Please note, the following is not implemented yet, but we are working on it.

Source code and data are versioned independendly from each other. Every data table uploaded to the Open Energy Platform contains a column 'version' which is used to identify different versions of the same data set. The version number is maintained for every table separately. This is a major difference to the versioning concept applied in the former data processing where all (interim) results were versioned under the same version number.

CHAPTER

THREE

GETTING STARTED

3.1 Pre-requisites

In addition to the installation of Python packages, some non-Python packages are required too. Right now these are:

- Docker: Docker is used to provide a PostgreSQL database (in the default case).

  Docker provides extensive installation instruction. Best you consult their docs and choose the appropriate install method for your OS.

  Docker is not required if you use a local PostreSQL installation.

- The *psql* executable. On Ubuntu, this is provided by the *postgresql-client-common* package.
- Header files for the `libpq5` PostgreSQL library. These are necessary to build the `psycopg2` package from source and are provided by the `libpq-dev` package on Ubuntu.
- osm2pgsql On recent Ubuntu version you can install it via `sudo apt install osm2pgsql`.
- postgis On recent Ubuntu version you can install it via `sudo apt install postgis`.
- osmTGmod resp. osmosis needs java. On recent Ubuntu version you can install it via `sudo apt install default-jre` and `sudo apt install default-jdk`.
- conda is needed for the subprocess of running pypsa-eur-sec. For the installation of miniconda, check out the conda installation guide.
- pypsa-eur-sec resp. Fiona needs the additional library `libtbb2`. On recent Ubuntu version you can install it via `sudo apt install libtbb2`
- gdal On recent Ubuntu version you can install it via `sudo apt install gdal-bin`.
- curl is required. You can install it via `sudo apt install curl`.
- To download ERA5 weather data you need to register at the CDS registration page and install the CDS API key as described here You also have to agree on the terms of use
- Make sure you have enough free disk space (~350 GB) in your working directory.

3.2 Installation

Since no release is available on PyPI and installations are probably used for development, cloning it via

```
git clone git@github.com:openego/eGon-data.git
```

and installing it in editable mode via

```
pip install -e eGon-data/
```

are recommended.

In order to keep the package installation isolated, we recommend installing the package in a dedicated virtual environment. There's both, an external tool and a builtin module which help in doing so. I also highly recommend spending the time to set up virtualenvwrapper to manage your virtual environments if you start having to keep multiple ones around.

If you run into any problems during the installation of `egon.data`, try looking into the list of known installation problems we have collected. Maybe we already know of your problem and also of a solution to it.

3.3 Run the workflow

The `egon.data` package installs a command line application called `egon-data` with which you can control the workflow so once the installation is successful, you can explore the command line interface starting with `egon-data --help`.

The most useful subcommand is probably `egon-data serve`. After running this command, you can open your browser and point it to *localhost:8080*, after which you will see the web interface of Apache Airflow with which you can control the eGo^n data processing pipeline.

If running `egon-data` results in an error, we also have collected a list of known runtime errors, which can consult in search of a solution.

To run the workflow from the CLI without using `egon-data serve` you can use

```
egon-data airflow scheduler
egon-data airflow dags trigger egon-data-processing-pipeline
```

For further details how to use the CLI see Apache Airflow CLI Reference.

Warning: A complete run of the workflow might require much computing power and can't be run on laptop. Use the *test mode* for experimenting.

Warning: A complete run of the workflow needs loads of free disk space (~350 GB) to store (temporary) files.

3.3.1 Test mode

The workflow can be tested on a smaller subset of data on example of the federal state of Schleswig-Holstein. Data is reduced during execution of the workflow to represent only this area.

Warning: Right now, the test mode is set in *egon.data/airflow/pipeline.py*.

CHAPTER

FOUR

TROUBLESHOOTING

Having trouble installing or running `eGon-data`? Here's a list of known issues including a solution.

4.1 Installation Errors

These are some errors you might encounter while trying to install *egon.data*.

4.1.1 importlib_metadata.PackageNotFoundError: No package metadata ...

It might happen that you have installed *importlib-metadata=3.1.0* for some reason which will lead to this error. Make sure you have *importlib-metadata>=3.1.1* installed. For more information read the discussion in issue #60.

4.2 Runtime Errors

These are some of the errors you might encounter while trying to run `egon-data`.

4.2.1 ERROR: Couldn't connect to Docker daemon ...

To verify, please execute `docker-compose -f <(echo {"service": {"image": "hellow-world"}}) ps` and you should see something like

```
ERROR: Couldn't connect to Docker daemon at http+docker://localunixsocket - is it␣
↪running?

If it's at a non-standard location, specify the URL with the DOCKER_HOST environment
variable.
```

This can have at least two possible reasons. First, the docker daemon might not be running. On Linux Systems, you can check for this by running `ps -e | grep dockerd`. If this generates no output, you have to start the docker daemon, which you can do via `sudo systemctl start docker.service` on recent Ubuntu systems.

Second, your current user might not be a member of the *docker* group. On Linux, you can check this by running `groups $(whoami)`. If the output does not contain the word *docker*, you have to add your current user to the *docker* group. You can find more information on how to do this in the docker documentation. Read the initial discussion for more context.

4.2.2 [ERROR] Connection in use ...

This error might arise when running `egon-data serve` making it shut down early with `ERROR - Shutting down webserver`. The reason for this is that the local webserver from a previous `egon-data serve` run didn't shut down properly and is still running. This can be fixed by running `ps -eo pid,command | grep "gunicorn: master" | grep -v grep` which should lead to output like `NUMBER gunicorn: master [airflow-webserver]` where `NUMBER` is a varying number. Once you got this, run `kill -s INT NUMBER`, substituting `NUMBER` with what you got previously. After this, `egon-data serve` should run without errors again.

4.2.3 [ERROR] Cannot create container for service egon-data-local-database ...

During building the docker container for the Postgres database, you might encounter an error like

```
ERROR: for egon-data-local-database  Cannot create container for service
egon-data-local-database: Conflict. The container name
"/egon-data-local-database" is already in use by container
"1ff9aadef273a76a0acbf850c0da794d0fb28a30e9840f818cca1a47d1181b00".
You have to remove (or rename) that container to be able to reuse that name.
```

If you're ok with deleting the data, stop and remove the container by

```
docker stop egon-data-local-database
docker rm -v egon-data-local-database
```

The container and its data can be kept by renaming the docker container.

```
docker rename egon-data-local-database NEW_CONTAINER_NAME
```

4.2.4 Working with multiple instances of egon-data

To make sure parallel installations of egon-data are not conflicting each other users have to set different values for the following options in the configuration:

```
--airflow-port
--compose-project-name
--database-port
--docker-container-name
```

4.3 Other import or incompatible package version errors

If you get an `ImportError` when trying to run `egon-data`, or the installation complains with something like

```
first-package a.b.c requires second-package>=q.r.r, but you'll have
second-package x.y.z which is incompatible.
```

you might have run into a problem of earlier `pip` versions. Either upgrade to a `pip` version >=20.3 and reinstall `egon.data`, or reinstall the package via `pip install -U --use-feature=2020-resolver`. The `-U` flag is important to actually force a reinstall. For more information read the discussions in issues #36 and #37.

CHAPTER

FIVE

DATA

The description of the methods, input data and results of the eGon-data pipeline is given in the following section. References to datasets and functions are integrated if more detailed information is required.

5.1 Main input data and their processing

All methods in the eGon-data workflow rely on public and freely available data from different external sources. The most important data sources and their processing within the eGon-data pipeline are described here.

5.1.1 Data bundle

The data bundle is published on zenodo. It contains several data sets, which serve as a basis for egon-data:

- Climate zones in Germany
- Data on eMobility individual trips of electric vehicles
- Spatial distribution of deep geothermal potentials in Germany
- Annual profiles in hourly resolution of electricity demand of private households
- Sample heat time series including hot water and space heating for single- and multi-familiy houses
- Hydrogen storage potentials in salt structures
- Information about industrial sites with DSM-potential in Germany
- Data extracted from the German grid development plan - power
- Parameters for the classification of gas pipelines
- Preliminary results from scenario generator pypsa-eur-sec
- German regions suitable to model dynamic line rating
- Eligible areas for wind turbines and ground-mounted PV systems
- Definitions of industrial and commercial branches
- Zensus data on households
- Geocoding of all unique combinations of ZIP code and municipality within the Marktstammdatenregister

For further description of the data including licenses and references please refer to the Zenodo repository.

5.1.2 Marktstammdatenregister

The Marktstammdatenregister (MaStR) is the register for the German electricity and gas market holding, among others, data on electricity and gas generation plants. In eGon-data it is used for status quo data on PV plants, wind turbines, biomass, hydro power plants, combustion power plants, nuclear power plants, geo- and solarthermal power plants, and storage units. The data are obtained from zenodo, where raw MaStR data, downloaded with the tool open-MaStR using the MaStR webservice, is provided. It contains all data from the MaStR, including possible duplicates. Currently, two versions are used:

- 2021-05-03
- 2022-11-17

The download is implemented in `MastrData`.

5.1.3 OpenStreetMap

OpenStreetMap (OSM) is a free, editable map of the whole world that is being built by volunteers and released with an open-content license. In eGon-data it is, among others, used to obtain information on land use as well as locations of buildings and amenities to spatially dissolve energy demand. The OSM data is downloaded from the Geofabrik download server, which holds extracts from the OpenStreetMap. Afterwards, they are imported to the database using osm2pgsql with a custom style file. The implementation of this can be found in *`OpenStreetMap`*.

In the *`OpenStreetMap`* dataset, the OSM data is filtered, processed and enriched with other data. This is described in the following subsections.

Amenity data

The data on amenities is used to disaggregate CTS demand data. It is filtered from the raw OSM data using tags listed in script *osm_amenities_shops_preprocessing.sql*, e.g. shops and restaurants. The filtered data is written to database table *openstreetmap.osm_amenities_shops_filtered*.

Building data

The data on buildings is required by several tasks in the pipeline, such as the disaggregation of household demand profiles or PV home systems to buildings, as well as the DIstribution Network Generat0r ding0 (see also ding0-grids).

The data processing steps are:

- Extract buildings and filter using relevant tags, e.g. residential and commercial, see script *osm_buildings_filter.sql* for the full list of tags. Resulting tables:
  - All buildings: *openstreetmap.osm_buildings*
  - Filtered buildings: *openstreetmap.osm_buildings_filtered*
  - Residential buildings: *openstreetmap.osm_buildings_residential*
- Create a mapping table for building's OSM IDs to the Zensus cells the building's centroid is located in. Resulting tables:
  - *boundaries.egon_map_zensus_buildings_filtered* (filtered)
  - *boundaries.egon_map_zensus_buildings_residential* (residential only)
- Enrich each building by number of apartments from Zensus table *society.egon_destatis_zensus_apartment_building_population_per_ha* by splitting up the cell's sum equally to the buildings. In some cases, a Zensus cell does not contain buildings but there is a building nearby which the

no. of apartments is to be allocated to. To make sure apartments are allocated to at least one building, a radius of 77m is used to catch building geometries.

- Split filtered buildings into 3 datasets using the amenities' locations: temporary tables are created in script *osm_buildings_temp_tables.sql*, the final tables in *osm_buildings_amentities_results.sql*. Resulting tables:
  - Buildings w/ amenities: *openstreetmap.osm_buildings_with_amenities*
  - Buildings w/o amenities: *openstreetmap.osm_buildings_without_amenities*
  - Amenities not allocated to buildings: *openstreetmap.osm_amenities_not_in_buildings*

As there are discrepancies between the Census data [Census] and OSM building data when both datasets are used to generate electricity demand profiles of households, synthetic buildings are added in Census cells with households but without buildings. This is done as part of the `Demand_Building_Assignment` dataset in function `generate_synthetic_buildings`. The synthetic building data are written to table *openstreetmap.osm_buildings_synthetic*. The same is done in case of CTS electricity demand profiles. Here, electricity demand is disaggregated to Census cells according to heat demand information from the Pan European Thermal Atlas [Peta]. In case there are Census cells with electricity demand assigned but no building or amenity data, synthetic buildings are added. This is done as part of the `CtsDemandBuildings` dataset in function `create_synthetic_buildings`. The synthetic building data are again written to table *openstreetmap.osm_buildings_synthetic*.

Street data

The data on streets is used in the DIstribution Network Generat0r ding0, e.g. for the routing of the grid. It is filtered from the raw OSM data using tags listed in script *osm_ways_preprocessing.sql*, e.g. highway=secondary. Additionally, each way is split into its line segments and their lengths is retained. The filtered streets data is written to database table *openstreetmap.osm_ways_preprocessed* and the filtered streets with segments to table *openstreetmap.osm_ways_with_segments*.

5.2 Grid models

Power grid models of different voltage levels form a central part of the eGon data model, which is required for cross-grid-level optimization. In addition, sector coupling necessitates the representation of the gas grid infrastructure, which is also described in this section.

5.2.1 Electricity grid

High and extra-high voltage grids

The model of the German extra-high (eHV) and high voltage (HV) grid is based on data retrieved from OpenStreetMap (status January 2021) [OSM] and additional parameters for standard transmission lines from [Brakelmann2004]. To gather all required information, such as line topology, voltage level, substation locations, and electrical parameters, to create a calculable power system model, the osmTGmod tool was used. The corresponding dataset `Osmtgmod` executes osmTGmod and writes the resulting data to the database.

The resulting grid model includes the voltage levels 380, 220 and 110 kV and all substations interconnecting these grid levels. For further information on the generation of the grid topology please refer to [Mueller2018].

Medium and low-voltage grids

Medium (MV) and low (LV) voltage grid topologies for entire Germany are generated using the python tool ding0 ding0. ding0 generates synthetic grid topologies based on high-resolution geodata and routing algorithms as well as typical network planning principles. The generation of the grid topologies is not part of eGon_data, but ding0 solely uses data generated with eGon_data, such as locations of HV/MV stations (see ehv-hv-grids), locations and peak demands of buildings in the grid (see building-data-ref respectively *Electricity*), as well as locations of generators from MaStR (see mastr-ref). A full list of tables used in ding0 can be found in its config. An exemplary MV grid with one underlying LV grid is shown in figure ding0-mv-grid. The grid data of all over 3.800 MV grids is published on zenodo.

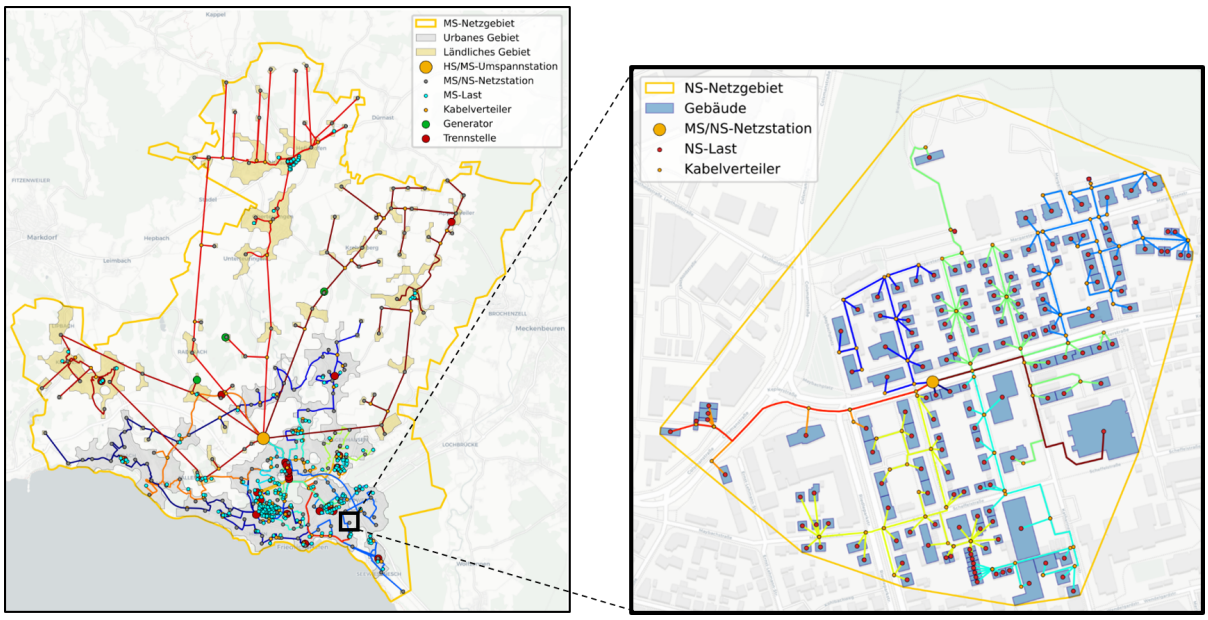


Fig. 1: Exemplary synthetic medium-voltage grid with underlying low-voltage grid generated with ding0

Besides data on buildings and generators, ding0 requires data on the supplied areas by each grid. This is as well done in eGon_data and described in the following.

MV grid districts

Medium-voltage (MV) grid districts describe the area supplied by one MV grid. They are defined by one polygon that represents the supply area. Each MV grid district is connected to the HV grid via a single substation. An exemplary MV grid district is shown in figure ding0-mv-grid (orange line).

The MV grid districts are generated in the dataset `MvGridDistricts`. The methods used for identifying the MV grid districts are heavily inspired by Hülk et al. (2017) [Huelk2017] (section 2.3), but the implementation differs in detail. The main difference is that direct adjacency is preferred over proximity. For polygons of municipalities without a substation inside, it is iteratively checked for direct adjacent other polygons that have a substation inside. Speaking visually, a MV grid district grows around a polygon with a substation inside.

The grid districts are identified using three data sources

1. Polygons of municipalities (`Vg250GemClean`)
2. Locations of HV-MV substations (`EgonHvmvSubstation`)
3. HV-MV substation voronoi polygons (`EgonHvmvSubstationVoronoi`)

Fundamentally, it is assumed that grid districts (supply areas) often go along borders of administrative units, in particular along the borders of municipalities due to the concession levy. Furthermore, it is assumed that one grid district is supplied via a single substation and that locations of substations and grid districts are designed for aiming least lengths of grid line and cables.

With these assumptions, the three data sources from above are processed as follows:

- Find the number of substations inside each municipality
- Split municipalities with more than one substation inside
  - Cut polygons of municipalities with voronoi polygons of respective substations
  - Assign resulting municipality polygon fragments to nearest substation
- Assign municipalities without a single substation to nearest substation in the neighborhood
- Merge all municipality polygons and parts of municipality polygons to a single polygon grouped by the assigned substation

For finding the nearest substation, as already said, direct adjacency is preferred over closest distance. This means, the nearest substation does not necessarily have to be the closest substation in the sense of beeline distance. But it is the substation definitely located in a neighboring polygon. This prevents the algorithm to find solutions where a MV grid districts consists of multi-polygons with some space in between. Nevertheless, beeline distance still plays an important role, as the algorithm acts in two steps

1. Iteratively look for neighboring polygons until there are no further polygons
2. Find a polygon to assign to by minimum beeline distance

The second step is required in order to cover edge cases, such as islands.

For understanding how this is implemented into separate functions, please see *define_mv_grid_districts*.

Load areas

Load areas (LAs) are defined as geographic clusters where electricity is consumed. They are used in ding0 to determine the extent and number of LV grids. Thus, within each LA there are one or multiple MV-LV substations, each supplying one LV grid. Exemplary load areas are shown in figure ding0-mv-grid (grey and orange areas).

The load areas are set up in the *LoadArea* dataset. The methods used for identifying the load areas are heavily inspired by Hülk et al. (2017) [Huelk2017] (section 2.4).

5.2.2 Gas grid

Information about the gas grids and how they were created

Methane grid

Hydrogen grid

5.3 Demand

Electricity, heat and gas demands from different consumption sectors are taken into account in eGon-data. The related methods to distribute and process the demand data are described in the following chapters for the different consumption sectors separately.

5.3.1 Electricity

Information about electricity demands and their spatial and temporal aggregation

5.3.2 Heat

Heat demands comprise space heating and dirinking hot water demands from residential and comertial trade and service (CTS) buildings. Process heat demands from the industry are, depending on the required temperature level, modelled as electrcity, hydrogen or methane demand.

The spatial distribution of annual heat demands is taken from the Pan-European Thermal Altlas version 5.0.1 [Peta]. This source provides data on annual european residential and CTS heat demands per hectar cell for the year 2015. In order to model future demands, the demand distribution extracted by Peta is then scaled to meet a national annual demand from external sources. The following national demands are taken for the selected scenarios:

Table 1: Heat demands per sector and scenario

	Residential sector	CTS sector	Sources
eGon2035	379 TWh	122 TWh	[Energiereferenzprognose]
eGon100RE	284 TWh	89 TWh	[Energiereferenzprognose]

The resulting data is stored in the database table *demand.egon_peta_heat*. The implementation of these dataprocessing steps can be found in *HeatDemandImport*.

Figure residential-heat-demand-annual shows the distribution of residential heat demands for scenario `eGon2035`, categorized for different levels of annual demands.

Afterwards, the annual heat demands are used to create hourly heat demand profiles. For residential heat demand profiles a pool of synthetical created bottom-up demand profiles is used. Depending on the mean temperature per day, these profiles are randomly assigned to each residential building. The methodology is described in detail in [Buettner2022].

Data on residential heat demand profiles is stored in the database within the tables *demand.egon_heat_timeseries_selected_profiles*, *demand.egon_daily_heat_demand_per_climate_zone*, *boundaries.egon_map_zensus_climate_zones*. To create the profiles for a selected buidling, these tables have to be combined, e.g. like this:

```
SELECT (b.demand/f.count * UNNEST(e.idp) * d.daily_demand_share)*1000 AS demand_profile
FROM (SELECT * FROM demand.egon_heat_timeseries_selected_profiles,
UNNEST(selected_idp_profiles) WITH ORDINALITY as selected_idp) a
JOIN demand.egon_peta_heat b
ON b.zensus_population_id = a.zensus_population_id
JOIN boundaries.egon_map_zensus_climate_zones c
ON c.zensus_population_id = a.zensus_population_id
JOIN demand.egon_daily_heat_demand_per_climate_zone d
ON (c.climate_zone = d.climate_zone AND d.day_of_year = ordinality)
JOIN demand.egon_heat_idp_pool e
ON selected_idp = e.index
JOIN (SELECT zensus_population_id, COUNT(building_id)
FROM demand.egon_heat_timeseries_selected_profiles
GROUP BY zensus_population_id
) f
ON f.zensus_population_id = a.zensus_population_id
WHERE a.building_id = SELECTED_BUILDING_ID
AND b.scenario = 'eGon2035'
AND b.sector = 'residential';
```

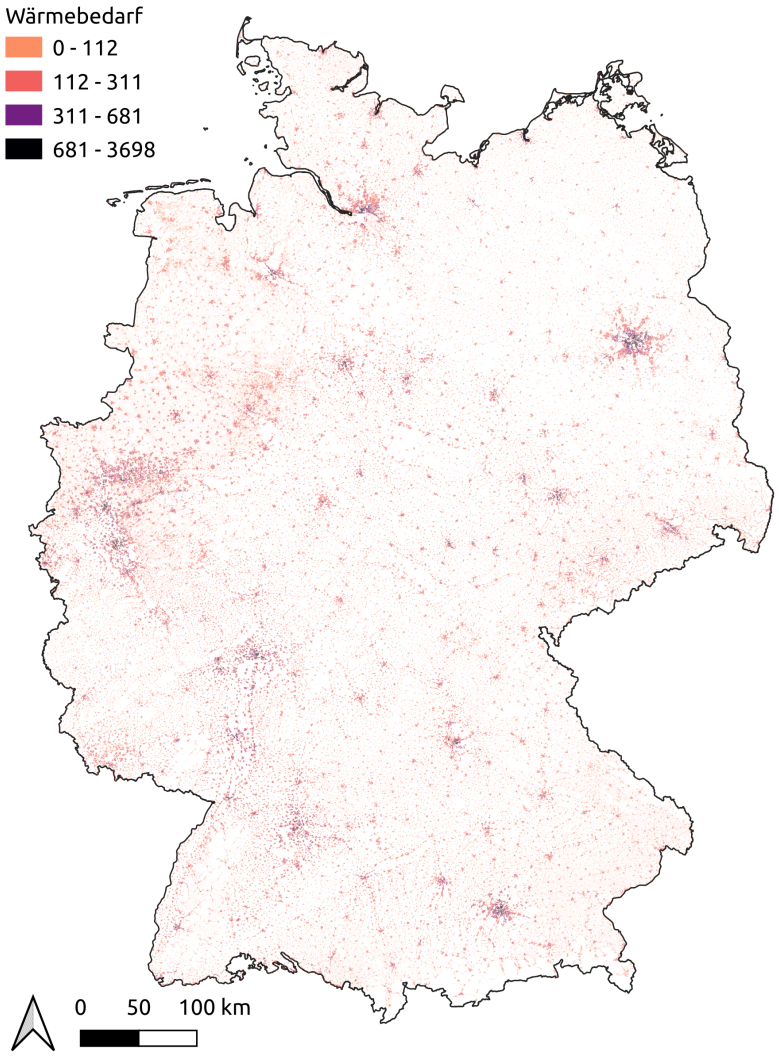


Fig. 2: Spatial distribution of residential heat demand in scenario eGon2035

Exemplary resulting residential heat demand time series for a selected day in winter and summer considering different aggregation levels are visualized in figures residential-heat-demand-timeseries-winter and residential-heat-demand-timeseries-summer.

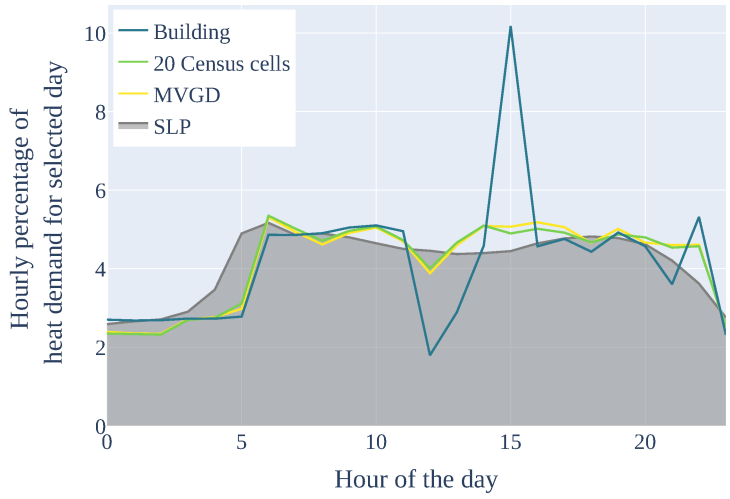


Fig. 3: Temporal distribution of residential heat demand for a selected day in winter

The temporal disaggregation of CTS heat demand is done using Standard Load Profiles Gas from `demandregio` [demandregio] considering different profiles per CTS branch.

The heat demand time series for both sectors creation is done in the Dataset *`HeatTimeSeries`*.

5.3.3 Gas

Information about gas demands and their spatial and temporal aggregation, including hydrogen and methane demands

5.3.4 Mobility

Motorized individual travel

The electricity demand data of motorized individual travel (MIT) for both the eGon2035 and eGon100RE scenario is set up in the *`MotorizedIndividualTravel`* dataset.

The profiles are generated using a modified version of SimBEV v0.1.3. SimBEV generates driving profiles for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) based on MID survey data [MiD2017] per RegioStaR7 region type [RegioStaR7_2020]. These profiles include driving, parking and (user-oriented) charging times. Different vehicle classes are taken into account whose assumed technical data is given in table ev-types-data. Moreover, charging probabilities for multiple types of charging infrastructure are presumed based on [NOW2020] and [Helfenbein2021]. Given these assumptions, a pool of 33.000 EVs-types is pre-generated and provided through the data bundle (see data-bundle-ref) as well as written to table *`EgonEvTrip`*. The complete tech data and assumptions of the run can be found in the metadata_simbev_run.json file, that is provided along with the trip data.

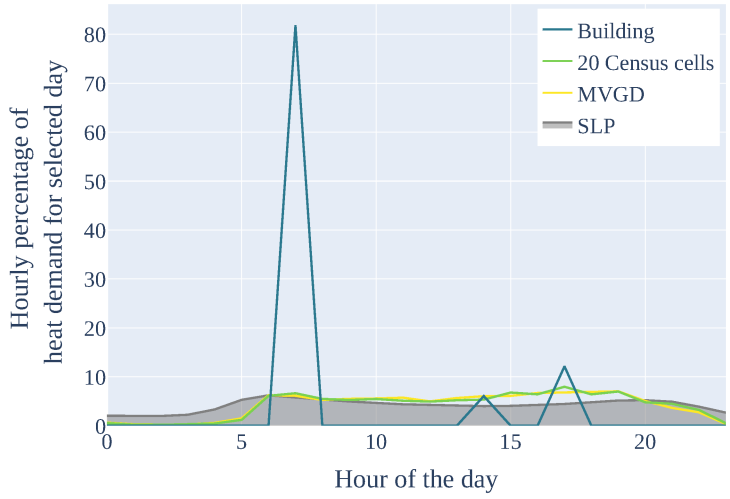


Fig. 4: Temporal distribution of residential heat demand for a selected day in summer

Table 2: EV types

Technology	Size	Max. charging capacity slow in kW	Max. charging capacity fast in kW	Battery capacity in kWh	Energy consumption in kWh/km
BEV	mini	11	120	60	0.1397
BEV	medium	22	350	90	0.1746
BEV	luxury	50	350	110	0.2096
PHEV	mini	3.7	40	14	0.1425
PHEV	medium	11	40	20	0.1782
PHEV	luxury	11	120	30	0.2138

Heavy-duty transport

In the context of the eGon project, it is assumed that all e-trucks will be completely hydrogen-powered. The hydrogen demand data of all e-trucks is set up in the `HeavyDutyTransport` dataset for both the eGon2035 and eGon100RE scenario.

In both scenarios the hydrogen consumption is assumed to be 6.68 kgH2 per 100 km with an additional supply chain leakage rate of 0.5 % (see here).

For the eGon2035 scenario the ramp-up figures are taken from the network development plan (version 2021) (Scenario C 2035). According to this, 100,000 e-trucks are expected in Germany in 2035, each covering an average of 100,000 km per year. In total this means 10 Billion km.

For the eGon100RE scenario it is assumed that the heavy-duty transport is completely hydrogen-powered. The total freight traffic with 40 Billion km is taken from the BMWK Langfristszenarien for heavy-duty vehicles larger 12 t allowed total weight (SNF > 12 t zGG).

The total hydrogen demand is spatially distributed on the basis of traffic volume data from [BASt]. For this purpose, first a voronoi partition of Germany using the traffic measuring points is created. Afterwards, the spatial shares of the Voronoi regions in each NUTS3 area are used to allocate hydrogen demand to the NUTS3 regions and are then aggregated per NUTS3 region. The refuelling is assumed to take place at a constant rate. Finally, to determine the hydrogen bus where the hydrogen demand is allocated to, the centroid of each NUTS3 region is used to determine the respective hydrogen Voronoi cell (see `GasAreaseGon2035` and `GasAreaseGon100RE`) it is located in.

5.4 Supply

The distribution and assignment of supply capacities or potentials are carried out technology-specific. The different methods are described in the following chapters.

5.4.1 Electricity

The electrical power plants park, including data on geolocations, installed capacities, etc. for the different scenarios is set up in the dataset `PowerPlants`.

Main inputs into the dataset are target capacities per technology and federal state in each scenario (see *Modeling concept and scenarios*) as well as the MaStR (see mastr-ref), OpenStreetMap (see osm-ref) and potential areas (provided through the data bundle, see data-bundle-ref) to distribute the generator capacities within each federal state region. The approach taken to distribute the target capacities within each federal state differs for the different technologies and is described in the following. The final distribution in the eGon2035 scenario is shown in figure generator-park-egon-2035.

Onshore wind

Offshore wind

PV ground mounted

PV rooftop

In a first step, the target capacity in the eGon2035 and eGon100RE scenarios is distributed to all MV grid districts linear to the residential and CTS electricity demands in the grid district (done in function `pv_rooftop_per_mv_grid`).

Afterwards, the PV rooftop capacity per MV grid district is disaggregated to individual buildings inside the grid district (done in function `pv_rooftop_to_buildings`). The basis for this is data from the MaStR, which is first cleaned and missing information inferred, and then allocated to specific buildings. New PV plants are in a last step added based on the capacity distribution from MaStR. These steps are in more detail described in the following.

MaStR data cleaning and inference:

- Drop duplicates and entries with missing critical data.
- Determine most plausible capacity from multiple values given in MaStR data.
- Drop generators that don't have a plausible capacity (23.5 MW > P > 0.1 kW).
- Randomly and weighted add a start-up date if it is missing.
- Extract zip and municipality from 'site' given in MaStR data.
- Geocode unique zip and municipality combinations with Nominatim (1 sec delay). Drop generators for which geocoding failed or which are located outside the municipalities of Germany.
- Add some visual sanity checks for cleaned data.

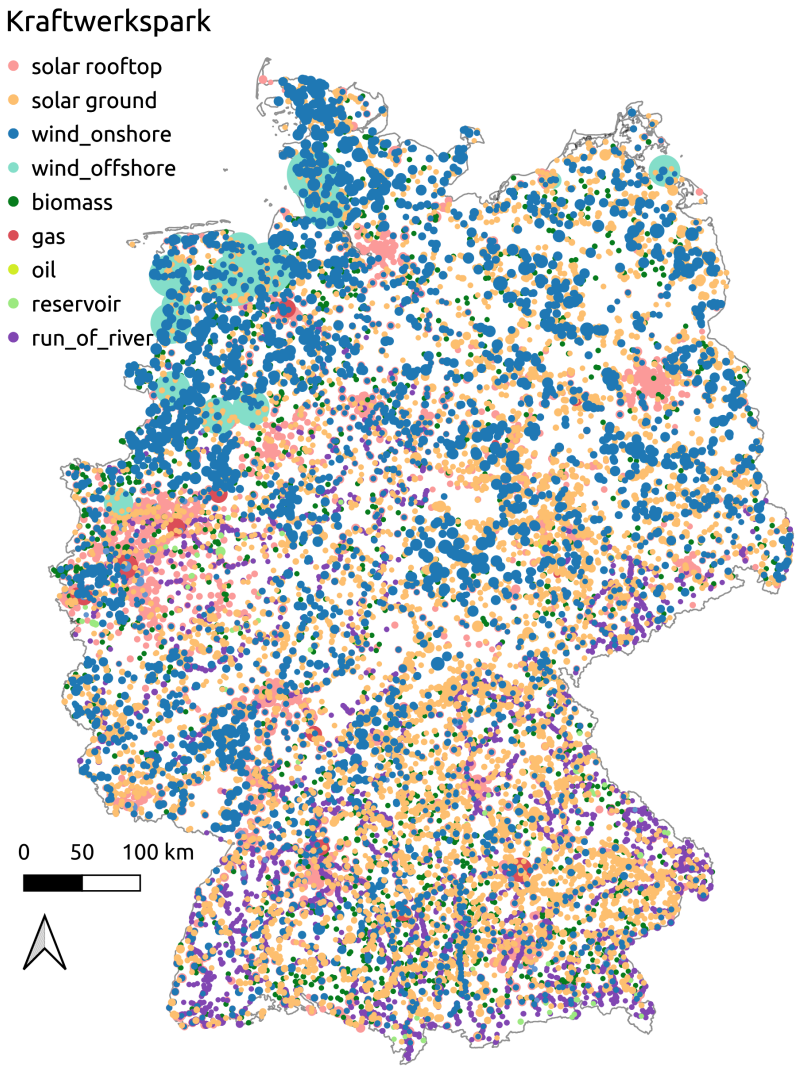


Fig. 5: Generator park in the eGon2035 scenario

Allocation of MaStR plants to buildings:

- Allocate each generator to an existing building from OSM or a synthetic building (see building-data-ref).
- Determine the quantile each generator and building is in depending on the capacity of the generator and the area of the polygon of the building.
- Randomly distribute generators within each municipality preferably within the same building area quantile as the generators are capacity wise.
- If not enough buildings exist within a municipality and quantile additional buildings from other quantiles are chosen randomly.

Disaggregation of PV rooftop scenario capacities:

- The scenario data per federal state is linearly distributed to the MV grid districts according to the PV rooftop potential per MV grid district.
- The rooftop potential is estimated from the building area given from the OSM buildings.
- Grid districts, which are located in several federal states, are allocated PV capacity according to their respective roof potential in the individual federal states.
- The disaggregation of PV plants within a grid district respects existing plants from MaStR, which did not reach their end of life.
- New PV plants are randomly and weighted generated using the capacity distribution of PV rooftop plants from MaStR.
- Plant metadata (e.g. plant orientation) is also added randomly and weighted using MaStR data as basis.

Hydro

5.4.2 Heat

Heat demand of residential as well as commercial, trade and service (CTS) buildings can be supplied by different technologies and carriers. Within the data model creation, capacities of supply technologies are assigned to specific locations and their demands. The hourly dispatch of heat supply is not part of the data model, but a result of the grid optimization tools.

In general, heat supply can be divided into three categories which include specific technologies: residential and CTS buildings in a district heating area, buildings supplied by individual heat pumps, and buildings supplied by conventional gas boilers. The shares of these categories are taken from external sources for each scenario.

Table 3: Heat demands of different supply categories

	District heating	Individual heat pumps	Individual gas boilers
eGon2035	69 TWh	27.24 TWh	390.78 TWh
eGon100RE	61.5 TWh	311.5 TWh	0 TWh

The following subsections describe the heat supply methodology for each category.

First, district heating areas are defined for each scenario based on existing district heating areas and an overall district heating share per scenario. To reduce the model complexity, district heating areas are defined per Census cell, either all buildings within a cell are supplied by district heat or none. The first step of the extraction of district heating areas is the identification of Census cells with buildings that are currently supplied by district heating using the `building` dataset of Census. All Census cells where more than 30% of the buildings are currently supplied by district heat are defined as cells inside a district heating area. The identified cells are then summarized by combining cells that have a maximum distance of 500m.

Second, additional Census cells are assigned to district heating areas considering the heat demand density. Assuming that new district heating grids are more likely in cells with high demand, the remaining Census cells outside of a district heating grid are sorted by their demands. Until the pre-defined national district heating demand is met, cells from that list are assigned to district heating areas. This can also result in new district heating grids which cover only a few Census cells.

To avoid unrealistic large district heating grids in areas with many cities close to each other (e.g. the Ruhr Area), district heating areas with an annual demand > 4 TWh are split by NUTS3 boundaries.

The implementation of the district heating area demarcation is done in *DistrictHeatingAreas*, the resulting data is stored in the tables *demand.egon_map_zensus_district_heating_areas* and *demand.egon_district_heating_areas*. The resulting district heating grids for the scenario eGon2035 are visualized in figure district-heating-areas, which also includes a zoom on the district heating grid in Berlin.

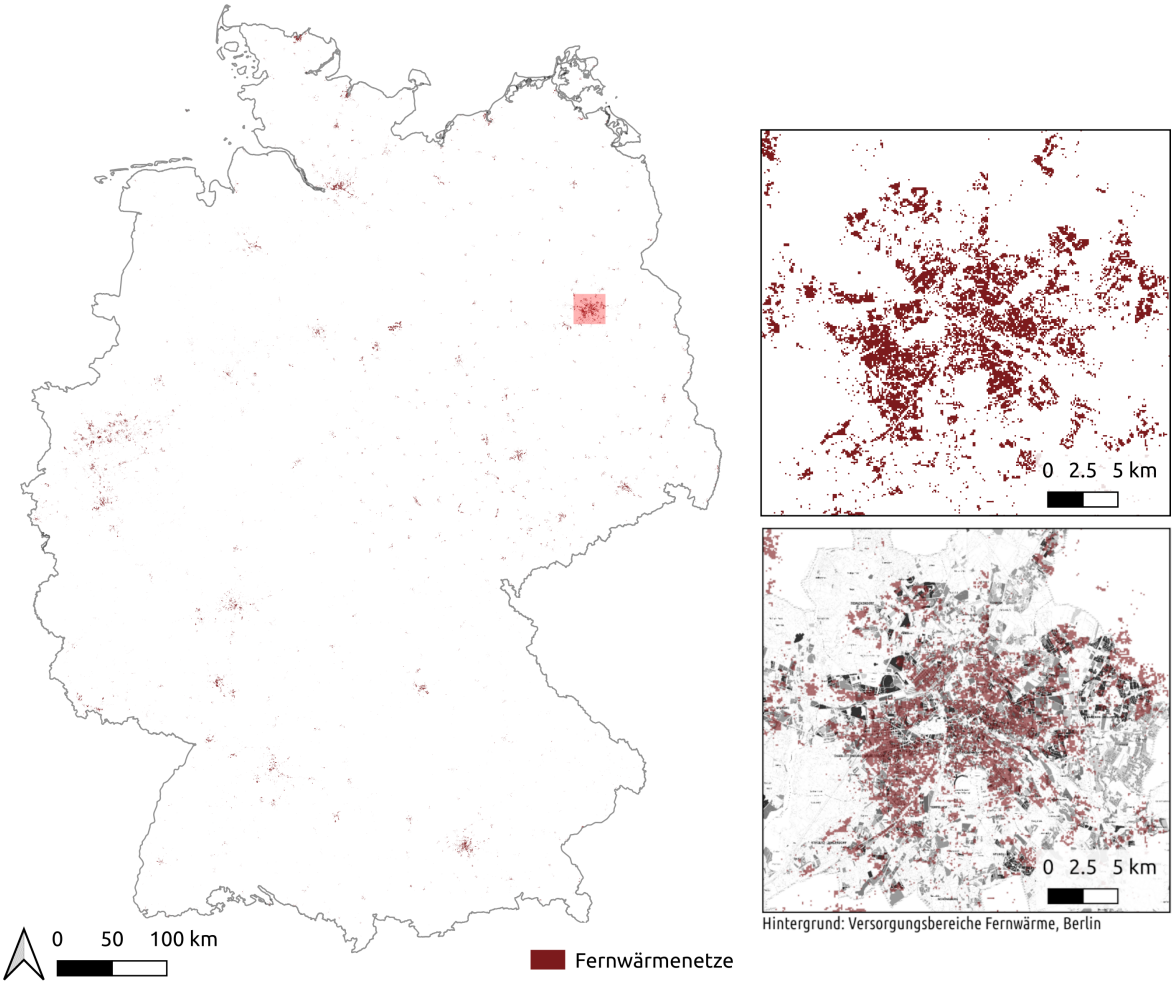


Fig. 6: Defined district heating grids in scenario `eGon2035`

The national capacities for each supply technology are taken from the Grid Development Plan (GDP) for the scenario `eGon2035`, in the `eGon100RE` scenario they are the result of the `pypsa-eur-sec` run. The distribution of the capacities to district heating grids is done similarly based on [FfE2017], which is also used in the GDP. The basic idea of this method is to use a cascade of heat supply technologies until the heat demand can be covered.

1. Combined heat and power (CHP) plants are assigned to nearby district heating grids first. Their location and thermal capacities are from Marktstammdatenregister [MaStR]. To identify district heating grids that need addi-

tional suppliers, the remaining annual heat demand is calculated using the thermal capacities of the CHP plants and assumed full load hours.

2. Large district heating grids with an annual demand that is higher than 96GWh can be supplied by geothermal plants, in case of an intersection of geothermal potential areas and the district heating grid. Smaller district heating grids can be supplied by solar thermal power plants. The national capacities are distributed proportionally to the remaining heat demands. After assigning these plants, the remaining heat demands are reduced by the thermal output and assumed full load hours.
3. Next, the national capacities for central heat pumps and resistive heaters are distributed to all district heating areas proportionally to their remaining demands. Heat pumps are modeled with a time-dependent coefficient of performance depending on the temperature data.
4. In the last step, gas boilers are assigned to every district heating grid regardless of the remaining demand. In the optimization, this can be used as a fall-back option to not run into infeasibilities.

The distribution of CHP plants for different carriers is shown in figure chp-plants.

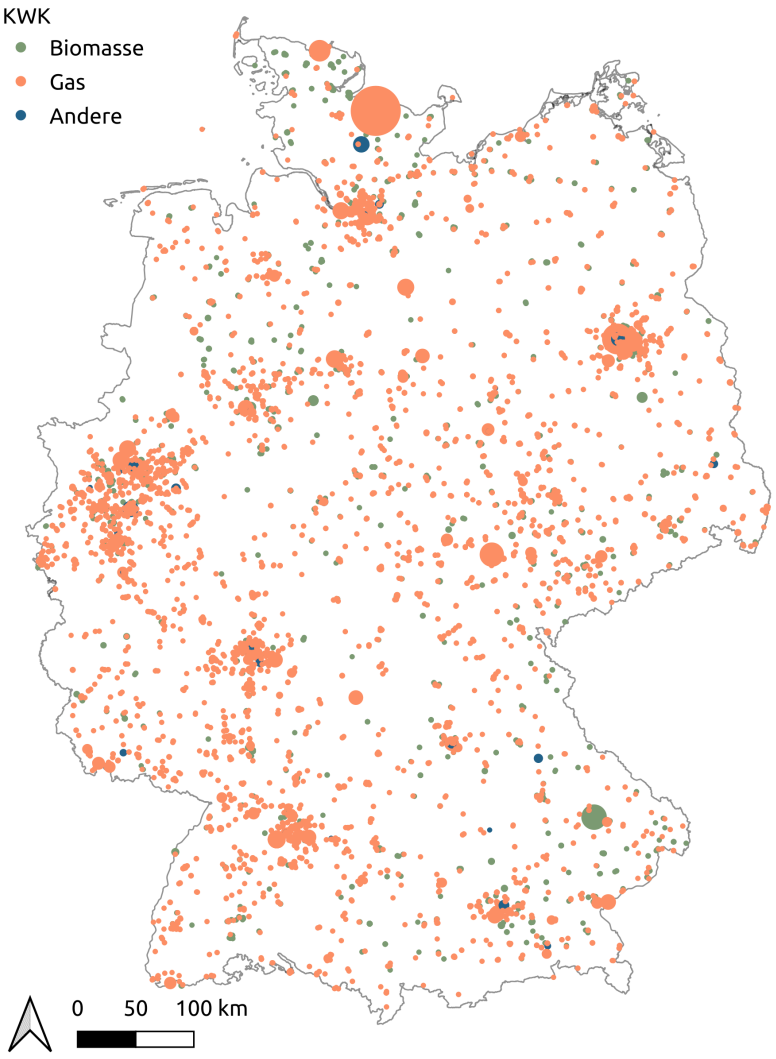


Fig. 7: Spatial distribution of CHP plants in scenario `eGon2035`

Heat pumps supplying individual buildings are first distributed to each medium-voltage grid district, these capacities

are later on further disaggregated to single buildings. Similar to central heat pumps they are modeled with a time-dependent coefficient of performance depending on the temperature data.

The distribution of the national capacities to each medium-voltage grid district is proportional to the heat demand outside of district heating grids.

@RLI: Distribution on building level

All residential and CTS buildings that are neither supplied by a district heating grid nor an individual heat pump are supplied by gas boilers. The demand time series of these buildings are multiplied by the efficiency of gas boilers and aggregated per methane grid node.

All heat supply categories are implemented in the dataset *HeatSupply*. The data is stored in the tables *demand.egon_district_heating* and *demand.egon_individual_heating*.

5.4.3 Gas

Information on gas supply - hydrogen and methane.

5.5 Flexibility options

Different flexibility options are part of the model and can be utilized in the optimization of the energy system. Therefore detailed information about flexibility potentials and their distribution are needed. The considered technologies described in the following chapters range from different storage units, through dynamic line rating to Demand-Side-Management measures.

5.5.1 Demand-Side-Management

How did we implement DSM? Results etc.

5.5.2 Dynamic line rating

To calculate the transmission capacity of each transmission line in the model, the procedure suggested in the **Principles for the Expansion Planning of the German Transmission Network** [NEP2021] where used:

1. Import the temperature and wind temporal raster layers from ERA-5. Hourly resolution data from the year 2011 was used. Raster resolution latitude-longitude grids at 0.25° x 0.25°.

2. Import shape file for the 9 regions proposed by the Principles for the Expansion Planning. See Figure 1.

Figure 1: Representative regions in Germany for DLR analysis [NEP2021]

3. Find the lowest wind speed in each region. To perform this, for each independent region, the wind speed of every cell in the raster layer should be extracted and compared. This procedure is repeated for each hour in the year 2011. The results are the 8760 lowest wind speed per region.

4. Find the highest temperature in each region. To perform this, for each independent region, the temperature of every cell in the raster layer should be extracted and compared. This procedure is repeated for each hour in the year 2011. The results are the 8760 maximum temperature per region.

5. Calculate the maximum capacity for each region using the parameters shown in Figure 2.

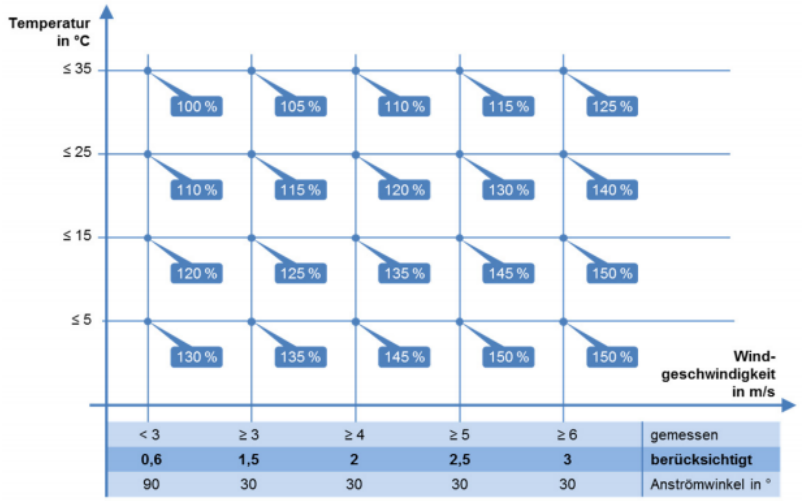


Figure 2: transmission capacity based on max temperature and min wind speed [NEP2021]

6. Assign the maximum capacity of the corresponding region to each transmission line inside each one of them. Crossborder lines and underground lines receive no values. It means that their capacities are static and equal to their nominal values. Lines that cross borders between regions receive the lowest capacity per hour of the regions containing the line.

5.5.3 E-Mobility

What flexibilities does e-mobility provide to the system. How did we implement it?

5.5.4 Battery stores

Battery storage units comprise home batteries and larger, grid-supportive batteries. National capacities for home batteries arise from external sources, e.g. the Grid Development Plan for the scenario `eGon2035`, whereas the capacities of large-scale batteries are a result of the grid optimization tool eTraGo.

Home battery capacities are first distributed to medium-voltage grid districts (MVGD) and based on that further disaggregated to single buildings. The distribution on MVGD level is done proportional to the installed capacities of solar rooftop power plants, assuming that they are used as solar home storage.

Potential large-scale batteries are included in the data model at every substation. The data model includes technical and economic parameters, such as efficiencies and investment costs. The energy-to-power ratio is set to a fixed value of 6 hours. Other central parameters are given in the following table

Table 4: Parameters of batteries for scenario eGon2035

	Value	Sources
Efficiency store	98 %	[DAE_store]
Efficiency dispatch	98 %	[DAE_store]
Standing loss	0 %	[DAE_store]
Investment costs	838 €/kW	[DAE_store]
Home storage units	16.8 GW	[?]

On transmission grid level, distinguishing between home batteries and large-scale batteries was not possible. Therefore, the capacities of home batteries were set as a lower boundary of the large-scale battery capacities. This is implemented

in the dataset *StorageEtrago*, the data for batteries in the transmission grid is stored in the database table *grid.egon_etrago_storage*.

5.5.5 Gas stores

Description of methods and assumptions to include potential h2 stores in the system

5.5.6 Hydrogen stores

5.5.7 Methane stores

5.5.8 Heat stores

The heat sector can provide flexibility through stores that allow shifting energy in time. The data model includes hot water tanks as heat stores in individual buildings and pit thermal energy storage for district heating grids (further described in district-heating).

Within the data model, potential locations as well as technical and economic parameters of these stores are defined. The installed store and (dis-)charging capacities are part of the grid optimization methods that can be performed by eTraGo. The power-to-energy ratio is not predefined but a result of the optimization, which allows to build heat stores with various time horizons.

Individual heat stores can be built in every building with an individual heat pump. Central heat stores can be built next to district heating grids. There are no maximum limits for the energy output as well as (dis-)charging capacities implemented yet.

Central cost assumptions for central and decentral heat stores are listed in the table below. The parameters can differ for each scenario in order to include technology updates and learning curves. The table focuses on the scenario `eGon2035`.

Table 5: Parameters of heat stores

	Technology	Costs for store capacity	Costs for (dis-)charging capacity	Round-trip efficiency	Sources
District heating	Pit thermal energy storage	0.51 EUR / kWh	0 EUR / kW	70 %	[DAE_store]
Buildings with heat pump	Water tank	1.84 EUR / kWh	0 EUR / kW	70 %	[DAE_store]

The heat stores are implemented as a part of the dataset *HeatEtrago*, the data is written into the tables *grid.egon_etrago_bus*, *grid.egon_etrago_link* and *grid.egon_etrago_store*.

5.6 Published data

CHAPTER

SIX

LITERATURE

CHAPTER

SEVEN

CONTRIBUTING

The research project eGo_n and egon-data are collaborative projects with several people contributing to it. The following section gives an overview of applicable guidelines and rules to enable a prospering collaboration. Any external contributions are welcome as well, and they are greatly appreciated! Every little bit helps, and credit will always be given.

7.1 Bug reports and feature requests

The best way to report bugs, inform about intended developments, send feedback or propose a feature is to file an issue at https://github.com/openego/eGon-data/issues.

Please tag your issue with one of the predefined labels as it helps others to keep track of unsolved bugs, open tasks and questions.

To inform others about intended developments please include: * a describtion of the purpose and the value it adds * outline the required steps for implementation * list open questions

When reporting a bug please include all information needed to reproduce the bug you found. This may include information on

- Your operating system name and version.
- Any details about your local setup that might be helpful in troubleshooting.
- Detailed steps to reproduce the bug.

If you are proposing a feature:

- Explain in detail how it would work.
- Keep the scope as narrow as possible, to make it easier to implement.

7.2 Contribution guidelines

7.2.1 Development

Adding changes to the egon-data repository should follow some guidelines:

1. Create an issue in our repository to describe the intended developments briefly
2. Create a branch for your issue related development from the dev-branch following our branch naming convention:

```
git checkout -b `<prefix>/#<issue-id>-very-brief-description`
```

where *issue-id* is the issue number on GitHub and *prefix* is one of

- features
- fixes
- refactorings

depending on which one is appropriate. This command creates a new branch in your local repository, in which you can now make your changes. Be sure to check out our *style conventions* so that your code is in line with them. If you don't have push rights to our repository, you need to fork it via the "Fork" button in the upper right of the repository page and work on the fork.

3. Make sure to update the documentation along with your code changes
4. When you're done making changes run all the checks and docs builder with tox one command:

```
tox
```

5. Commit your changes and push your branch to GitHub:

```
git add -p
git commit
git push origin features/#<issue-id>-very-brief-description
```

Note that the `-p` switch will make `git add` iterate through your changes and prompt for each one on whether you want to include it in the upcoming commit. This is useful if you made multiple changes which should conceptually be grouped into different commits, like e.g. fixing the documentation of one function and changing the implementation of an unrelated one in parallel, because it allows you to still make separate commits for these changes. It has the drawback of not picking up new files though, so if you added files and want to put them under version control, you have to add them explicitly by running `git add FILE1 FILE2 ...` instead.

6. Submit a pull request through the GitHub website.

7.2.2 Code and Commit Style

We try the adhere to the PEP 8 Style Guide wherever possible. In addition to that, we use *a code formatter* to have a consistent style, even in cases where PEP 8 leaves multiple degrees of freedom. So please run your code through `black` before committing it.[1] PEP 8 also specifies a way to group imports, onto which we put the additional constraint that the imports within each group are ordered alphabetically. Once again, you don't have to keep track of this manually, but you can use isort to have imports sorted automatically. Note that *pre-commit* hooks are configured for this repository, so you can just `pip install pre-commit` followed by `pre-commit install` in the repository, and every commit will automatically be checked for style violations.

Unfortunately these tools don't catch everything, so here's a short list of things you have to keep track of manually:

- `Black` can't automatically break up overly long strings, so make use of Python's automatic string concatenation feature by e.g. converting

```
something = "A really really long string"
```

into the equivalent:

[1] If you want to be really nice, run any file you touch through `black` before making changes, and commit the result separately from other changes.. The repository may contain wrongly formatted legacy code, and this way you commit eventually necessary style fixes separated from your actually meaningful changes, which makes the reviewers job a lot easier.

```
something = (
    "A really really"
    " long string"
)
```

- `Black` also can't check whether you're using readable names for your variables. So please don't use abbreviations. Use readable names.
- `Black` also can't reformat your comments. So please keep in mind that PEP 8 specifies a line length of 72 for free flowing text like comments and docstrings. This also extends to the documentation in reStructuredText files.

Last but not least, commit messages are a kind of documentation, too, which should adhere to a certain style. There are quite a few documents detailing this style, but the shortest and easiest to find is probably https://commit.style. If you have 15 minutes instead of only five to spare, there's also a very good and only slightly longer article on this subject, containing references to other style guides, and also explaining why commit messages are important.

At the very least, try to only commit small, related changes. If you have to use an "and" when trying to summarize your changes, they should probably be grouped into separate commits.

7.2.3 Pull Request Guidelines

We use pull requests (PR) to integrate code changes from branches. PRs always need to be reviewed (exception proves the rule!). Therefore, ask one of the other developers for reviewing your changes. Once approved, the PR can be merged. Please delete the branch after merging.

Before requesting a review, please

1. Include passing tests (run `tox`).[2]
2. Let the workflow run in *Test mode* once from scratch to verify successful execution
3. Make sure that your changes are tested in integration with other tasks and on a complete run at least once by merging them into the continuous-integration/run-everything-over-the-weekend branch. This branch will regularly be checked out and tested on a complete workflow run on friday evening.
4. Update documentation when there's new API, functionality etc.
5. Add a note to `CHANGELOG.rst` about the changes and refer to the corresponding Github issue.
6. Add yourself to `AUTHORS.rst`.

When requesting reviews, please keep in mind it might be a significant effort to review the PR. Try to make it easier for them and keep the overall effort as low as possible. Therefore,

- asking for reviewing specific aspects helps reviewers a lot to focus on the relevant parts
- when multiple people are asked for a review it should be avoided that they check/test the same things. Be even more specific what you expect from someone in particular.

[2] If you don't have all the necessary Python versions available locally you can rely on CI via GitHub actions - it will run the tests for each change you add in the pull request.
It will be slower though …

7.2.4 What needs to be reviewed?

Things that definitely should be checked during a review of a PR:

- *Is the code working?* The contributor should already have made sure that this is the case. Either by automated test or manual execution.
- *Is the data correct?* Verifying that newly integrated and processed data is correct is usually not possible during reviewing a PR. If it is necessary, please ask the reviewer specifically for this.
- *Do tests pass?* See automatic checks.
- *Is the documentation up-to-date?* Please check this.
- *Was* `CHANGELOG.rst` *updated accordingly?* Should be the case, please verify.
- *Is metadata complete and correct (in case of data integration)?* Please verify. In case of a pending metadata creation make sure an appropriate issue is filed.

7.3 Extending the data workflow

The egon-data workflow uses Apache Airflow which organizes the order of different processing steps and their execution.

7.3.1 How to add Python scripts

To integrate a new Python function to the egon-data workflow follow the steps listed:

1. Add your well documented script to the egon-data repository
2. Integrate functions which need to be called within the workflow to pipeline.py, which organzies and calls the different tasks within the workflow
3. Define the interdependencies between the scripts by setting the task downstream to another required task
4. The workflow can now be triggered via Apache Airflow

7.3.2 Where to save (downloaded) data?

If a task requires to retrieve some data from external sources which needs to be saved locally, please use *CWD* to store the data. This is achieved by using

```
from pathlib import Path
from urllib.request import urlretrieve

filepath = Path(".") / "filename.csv"
urlretrieve("https://url/to/file", filepath)
```

7.3.3 Add metadata

Add a metadata for every dataset you create for describing data with machine-readable information. Adhere to the OEP Metadata v1.4.1, you can follow the example to understand how the fields are used. Field are described in detail in the Open Energy Metadata Description.

You can obtain the metadata string from a table you created in SQL via

```
SELECT obj_description('<SCHEMA>.<TABLE>'::regclass);
```

Alternatively, you can write the table comment directly to a JSON file by

```
psql -h <HOST> -p <PORT> -d <DB> -U <USER> -c "\COPY (SELECT obj_description('<SCHEMA>.
↪<TABLE>'::regclass)) TO '/PATH/TO/FILE.json';"
```

For bulk export of all DB's table comments you can use this script. Please verify that your metadata string is in compliance with the OEP Metadata standard version 1.4.1 using the OMI tool (tool is shipped with eGon-data):

```
omi translate -f oep-v1.4 -t oep-v1.4 metadata_file.json
```

If your metadata string is correct, OMI puts the keys in the correct order and prints the full string (use *-o* option for export).

You may omit the fields *id* and *publicationDate* in your string as it will be automatically set at the end of the pipeline but you're required to set them to some value for a complete validation with OMI. For datasets published on the OEP *id* will be the URL which points to the table, it will follow the pattern *https://openenergy-platform.org/dataedit/view/SCHEMA/TABLE*.

For previous discussions on metadata, you may want to check PR 176.

Helpers

You can use the Metadata creator **GUI**. Fill the fields and hit *Edit JSON* to get the metadata string. Vice versa, you can paste a metadata string into this box and the fields will be filled automatically which may be helpful if you want to amend existing strings.

There are some **licence templates** provided in *egon.data.metadata* you can make use of for fields 11.4 and 12 of the Open Energy Metadata Description. Also, there's a template for the **metaMetadata** (field 16).

There are some functions to quickly generate a template for the **resource fields** (field 14.6.1 in Open Energy Metadata Description) from a SQLA table class or a DB table. This might be especially helpful if your table has plenty of columns.

- From SQLA table class: *egon.data.metadata.generate_resource_fields_from_sqla_model()*
- From database table: *egon.data.metadata.generate_resource_fields_from_db_table()*

Sources

The **sources** (field 11) are the most important parts of the metadata which need to be filled manually. You may also add references to tables in eGon-data (e.g. from an upstream task) so you don't have to list all original sources again. Make sure you include all upstream attribution requirements.

The following example uses various input datasets whose attribution must be retained:

```
"sources": [
    {
        "title": "eGo^n - Medium voltage grid districts",
        "description": (
            "Medium-voltage grid districts describe the area supplied by "
            "one MV grid. Medium-voltage grid districts are defined by one "
            "polygon that represents the supply area. Each MV grid district "
            "is connected to the HV grid via a single substation."
        ),
        "path": "https://openenergy-platform.org/dataedit/view/"
                "grid/egon_mv_grid_district", # "id" in the source dataset
        "licenses": [
            license_odbl(attribution=
                "© OpenStreetMap contributors, 2021; "
                "© Statistische Ämter des Bundes und der Länder, 2014; "
                "© Statistisches Bundesamt, Wiesbaden 2015; "
                "(Daten verändert)"
            )
        ]
    },
    # more sources...
]
```

7.3.4 Adjusting test mode data

When integrating new data or data processing scripts, make sure the *Test mode* still works correctly on a limited subset of data. In particular, if a new external data sources gets integrated make sure the data gets cut to the region of the test mode.

7.4 Documentation

eGon-data could always use more documentation, whether as part of the official eGon-data docs, in docstrings, or even in articles, blog posts or similar resources. Always keep in mind to update the documentation along with your code changes though.

The changes of the documentation in a feature branch get visible once a pull request is opened.

7.4.1 How to document Python scripts

Use docstrings to document your Python code. Note that PEP 8 also contains a section on docstrings and that there is a whole PEP dedicated to docstring conventions. Try to adhere to both of them. Additionally every Python script needs to contain a header describing the general functionality and objective and including information on copyright, license and authors.

```
""" Provide an example of the first line of a module docstring.

This is an example header describing the functionalities of a Python
script to give the user a general overview of what's happening here.
"""


__copyright__ = "Example Institut"
__license__ = "GNU Affero General Public License Version 3 (AGPL-3.0)"
__url__ = "https://github.com/openego/eGon-data/blob/main/LICENSE"
__author__ = "github_alias1, github_alias2"
```

7.4.2 How to document SQL scripts

Please also add a similar header to your SQL scripts to give users and fellow developers an insight into your scripts and the methodologies applied. Please describe the content and objectives of the script briefly but as detailed as needed to allow other to comprehend how it works.

```
/*
This is an example header describing the functionalities of a SQL
script to give the user a general overview what's happening here

__copyright__ = "Example Institut"
__license__ = "GNU Affero General Public License Version 3 (AGPL-3.0)"
__url__ = "https://github.com/openego/eGon-data/blob/main/LICENSE"
__author__ = "github_alias1, github_alias2"
*/
```

You can build the documentation locally with (executed in the repos root directory)

```
sphinx-build -E -a docs docs/_build/
```

Eventually, you might need to install additional dependencies for building the documenmtation:

```
pip install -r docs/requirements.txt
```

7.4.3 Tips

To run a subset of tests:

```
tox -e envname -- pytest -k test_myfeature
```

To run all the test environments in *parallel*:

```
tox -p auto
```

CHAPTER

EIGHT

AUTHORS

- Guido Pleßmann, Ilka Cußmann, Stephan Günther, Jonathan Amme, Julian Endres, Kilian Helfenbein - https://github.com/openego/eGon-data

CHAPTER

NINE

CHANGELOG

9.1 Unreleased

9.1.1 Added

- Include description of the egon-data workflow in our documentation #23
- There's now a wrapper around *subprocess.run* in *egon.data.subprocess.run*. This wrapper catches errors better and displays better error messages than Python's built-in function. Use this wrapper wenn calling other programs in Airflow tasks.
- You can now override the default database configuration using command line arguments. Look for the switches starting with `--database` in `egon-data --help`. See PR #159 for more details.
- Docker will not be used if there is already a service listening on the HOST:PORT combination configured for the database.
- You can now supply values for the command line arguments for `egon-data` using a configuration file. If the configuration file doesn't exist, it will be created by `egon-data` on it's first run. Note that the configuration file is read from and written to the direcctory in which `egon-data` is started, so it's probably best to run `egon-data` in a dedicated directory. There's also the new function *egon.data.config.settings* which returns the current configuration settings. See PR #159 for more details.
- You can now use tasks which are not part of a `Dataset`, i.e. which are unversioned, as dependencies of a dataset. See **`PR #318`_** for more details.
- You can now force the tasks of a `Dataset` to be always executed by giving the version of the `Dataset` a `".dev"` suffix. See **`PR #318`_** for more details.
- OSM data import as done in open_ego #1 which was updated to the latest long-term data set of the 2021-01-01 in #223
- Verwaltungsgebiete data import (vg250) more or less done as in open_ego #3
- Zensus population data import #2
- Zensus data import for households, apartments and buildings #91
- DemandRegio data import for annual electricity demands #5
- Download cleaned open-MaStR data from Zenodo #14
- NEP 2021 input data import #45
- Option for running workflow in test mode #112
- Abstraction of hvmv and ehv substations #9
- Filter zensus being inside Germany and assign population to municipalities #7

- RE potential areas data import #124
- Heat demand data import #101
- Demographic change integration #47
- Creation of voronoi polygons for hvmv and ehv substations #9
- Add hydro and biomass power plants eGon2035 #127
- Creation of the ehv/hv grid model with osmTGmod, see issue #4 and PR #164
- Identification of medium-voltage grid districts #10
- Distribute electrical demands of households to zensus cells #181
- Distribute electrical demands of cts to zensus cells #210
- Include industrial sites' download, import and merge #117
- Integrate scenario table with parameters for each sector #177
- The volume of the docker container for the PostgreSQL database is saved in the project directory under *docker/database-data*. The current user (*$USER*) is owner of the volume. Containers created prior to this change will fail when using the changed code. The container needs to be re-created. #228
- Extract landuse areas from OSM #214
- Integrate weather data and renewable feedin timeseries #19
- Create and import district heating areas #162
- Integrate electrical load time series for cts sector #109
- Assign voltage level and bus_id to power plants #15
- Integrate solar rooftop for etrago tables #255
- Integrate gas bus and link tables #198
- Integrate data bundle #272
- Add household electricity demand time series, mapping of demand profiles to census cells and aggregated household electricity demand time series at MV grid district level #256
- Integrate power-to-gas installation potential links #293
- Integrate distribution of wind onshore and pv ground mounted generation #146
- Integrate dynamic line rating potentials #72
- Integrate gas voronoi polygons #308
- Integrate supply strategies for individual and district heating #232
- Integrate gas production #321
- Integrate industrial time series creation #237
- Merge electrical loads per bus and export to etrago tables #328
- Insert industial gas demand #358
- Integrate existing CHP and extdended CHP > 10MW_el #266
- Add random seed to CLI parameters #351
- Extend zensus by a combined table with all cells where there's either building, apartment or population data #359

- Include allocation of pumped hydro units #332
- Add example metadata for OSM, VG250 and Zensus VG250. Add metadata templates for licences, context and some helper functions. Extend docs on how to create metadata for tables. #139
- Integrate DSM potentials for CTS and industry #259
- Assign weather cell id to weather dependant power plants #330
- Distribute wind offshore capacities #329
- Add CH4 storages #405
- Include allocation of conventional (non CHP) power plants #392
- Fill egon-etrago-generators table #485
- Include time-dependent coefficient of performance for heat pumps #532
- Limit number of parallel processes per task #265
- Include biomass CHP plants to eTraGo tables #498
- Include Pypsa default values in table creation #544
- Include PHS in eTraGo tables #333
- Include feedin time series for wind offshore #531
- Include carrier names in eTraGo table #551
- Include hydrogen infrastructure for eGon2035 scenario #474
- Include downloaded pypsa-eur-sec results #138
- Create heat buses for eGon100RE scenario #582
- Filter for DE in gas infrastructure deletion at beginning of respective tasks #567
- Insert open cycle gas turbines into eTraGo tables #548
- Preprocess buildings and amenities for LV grids #262
- Assign household profiles to OSM buildings #435
- Add link to meta creator to docs #599
- Add extendable batteries and heat stores #566
- Add efficiency, capital_cost and marginal_cost to gas related data in etrago tables #596
- Add wind onshore farms for the eGon100RE scenario #690
- The shared memory under *"/dev/shm"* is now shared between host and container. This was done because Docker has a rather tiny default for the size of *"/dev/shm"* which caused random problems. Guessing what size is correct is also not a good idea, so sharing between host and container seems like the best option. This restricts using *egon-data* with docker to Linux and MacOS, if the latter has *"/dev/shm"* but seems like the best course of action for now. Done via PR #703 and hopefully prevents issues #702 and #267 from ever occurring again.
- Provide wrapper to catch DB unique violation #514
- Add electric scenario parameters for eGon100RE #699
- Introduce Sanity checks for eGon2035 #382
- Add motorized individual travel #553
- Allocating MaStR PV rooftop power plants to OSM and synthetic buildings. Desaggregating PV rooftop scenarios to mv grid districts and OSM and synthetic buildings. #684

- Add mapping zensus - weather cells #845
- Add pv rooftop plants per mv grid for eGon100RE #861
- Integrated heavy duty transport FCEV #552
- Assign CTS demands to buildings #671
- Add sanity checks for residential electricity loads #902
- Add sanity checks for cts loads #919
- Add distribution of CHP plants for eGon100RE #851
- Add mapping table for all used buildings #962
- Add charging infrastructure for e-mobility #937
- Add zipfile check #969
- Add marginal costs for generators abroad and for carriers nuclear and coal #907
- Add wind off shore power plants for eGon100RE #868
- Write simBEV metadata to DB table PR #978
- Add voltage level for electricity building loads #955
- Add desaggregation of pv home batteries onto buildings #988
- Desaggregation of DSM time series onto CTS consumers per bus id and individual indutry consumers. #1048
- Add load areas #1014
- Add new MaStR dataset #1051
- Heat pump desaggregation to buildings PR #903
- Add low flex scenario 'eGon2035_lowflex' #822
- Add MaStR geocoding and handling of conventional generators #1095

9.1.2 Changed

- Adapt structure of the documentation to project specific requirements #20
- Switch from Travis to GitHub actions for CI jobs #92
- Rename columns to id and zensus_population_id in zensus tables #140
- Revise docs CONTRIBUTING section and in particular PR guidelines #88 and #145
- Drop support for Python3.6 #148
- Improve selection of zensus data in test mode #151
- Delete tables before re-creation and data insertation #166
- Adjust residential heat demand in unpopulated zenus cells #167
- Introduce mapping between VG250 municipalities and census cells #165
- Delete tables if they exist before re-creation and data insertation #166
- Add gdal to pre-requisites #185
- Update task zensus-inside-germany #196
- Update installation of demandregio's disaggregator #202

- Update etrago tables #243 and #285
- Migrate VG250 to datasets #283
- Allow configuring the airflow port #281
- Migrate mastr, mv_grid_districts and re_potential_areas to datasets #297
- Migrate industrial sites to datasets #237
- Rename etrago tables from e.g. egon_pf_hv_bus to egon_etrago bus etc. #334
- Move functions used by multiple datasets #323
- Migrate scenario tables to datasets #309
- Migrate weather data and power plants to datasets #314
- Create and fill table for CTS electricity demand per bus #326
- Migrate osmTGmod to datasets #305
- Filter osm landuse areas, rename industrial sites tables and update load curve function #378
- Remove version columns from eTraGo tables and related code #384
- Remove country column from scenario capacities table #391
- Update version of zenodo download #397
- Rename columns gid to id #169
- Remove upper version limit of pandas #383
- Use random seed from CLI parameters for CHP and society prognosis functions #351
- Changed demand.egon_schmidt_industrial_sites - table and merged table (industrial_sites) #423
- Replace ‘gas’ carrier with ‘CH4’ and ‘H2’ carriers #436
- Adjust file path for industrial sites import #418
- Rename columns subst_id to bus_id #335
- Apply black and isort for all python scripts #463
- Update deposit id for zenodo download #498
- Add to etrago.setug.py the busmap table #484
- Migrate dlr script to datasets #508
- Migrate loadarea scripts to datasets #525
- Migrate plot.py to dataset of district heating areas #527
- Migrate substation scripts to datasets #304
- Update deposit_id for zenodo download #540
- Add household demand profiles to etrago table #381
- Migrate zensus scripts to datasets #422
- Add information on plz, city and federal state to data on mastr without chp #425
- Assign residential heat demands to osm buildings #557
- Add foreign gas buses and adjust cross bording pipelines #545
- Integrate fuel and CO2 costs for eGon2035 to scenario parameters #549

- Aggregate generators and stores for CH4 #629
- Fill missing household data for populated cells #431
- Fix RE potential areas outside of Germany by updating the dataset. Import files from data bundle. #592 #595
- Add DC lines from Germany to Sweden and Denmark #611
- H2 demand is met from the H2_grid buses. In Addtion, it can be met from the H2_saltcavern buses if a proximity criterion is fulfilled #620
- Create H2 pipeline infrastructure for eGon100RE #638
- Change refinement method for households types #651
- H2 feed in links are changed to non extendable #653
- Remove the '_fixed' suffix #628
- Fill table demand.egon_demandregio_zensus_electricity after profile allocation #586
- Change method of building assignment #663
- Create new OSM residential building table #587
- Move python-operators out of pipeline #644
- Add annualized investment costs to eTraGo tables #672
- Improve modelling of NG and biomethane production #678
- Unify carrier names for both scenarios #575
- Add automatic filtering of gas data: Pipelines of length zero and gas buses isolated of the grid are deleted. #590
- Add gas data in neighbouring countries #727
- Aggregate DSM components per substation #661
- Aggregate NUTS3 industrial loads for CH4 and H2 #452
- Update OSM dataset from 2021-02-02 to 2022-01-01 #486
- Update deposit id to access v0.6 of the zenodo repository #627
- Include electricity storages for eGon100RE scenario #581
- Update deposit id to access v0.7 of the zenodo repository #736
- Include simplified restrictions for H2 feed-in into CH4 grid #790
- Update hh electricity profiles #735
- Improve CH4 stores and productions aggregation by removing dedicated task #775
- Add CH4 stores in Germany for eGon100RE #779
- Assigment of H2 and CH4 capacitites for pipelines in eGon100RE #686
- Update deposit id to access v0.8 of the zenodo repository #760
- Add primary key to table openstreetmap.osm_ways_with_segments #787
- Update pypsa-eur-sec fork and store national demand time series #402
- Move and merge the two assign_gas_bus_id functions to a central place #797
- Add coordinates to non AC buses abroad in eGon100RE #803
- Integrate additional industrial electricity demands for eGon100RE #817

- Set non extendable gas components from p-e-s as so for eGon100RE #877
- Integrate new data bundle using zenodo sandbox #866
- Add noflex scenario for motorized individual travel #821
- Allocate PV home batteries to mv grid districts #749
- Add sanity checks for motorized individual travel #820
- Parallelize sanity checks #882
- Insert crossboarding gas pipeline with Germany in eGon100RE #881
- Harmonize H2 carrier names in eGon100RE #929
- Rename noflex to lowflex scenario for motorized individual travel #921
- Update creation of heat demand timeseries #857 #856
- Overwrite retrofitted_CH4pipeline-to-H2pipeline_share with pes result #933
- Adjust H2 industry profiles abroad for eGon2035 #940
- Introduce carrier name 'others' #819
- Add rural heat pumps per medium voltage grid district #987
- Add eGon2021 scenario to demandregio dataset #1035
- Update MaStR dataset #519
- Add missing VOM costs for heat sector components #942
- Add sanity checks for gas sector in eGon2035 #864
- Desaggregate industry demands to OSM areas and industrial sites #1001
- Add gas generator in Norway #1074
- SQLAlchemy *engine* objects created via `egon.data.db.engine` are now cached on a per process basis, so only one *engine* is ever created for a single process. This fixes issue #799.
- Insert rural heat per supply technology #1026
- Insert lifetime for components from p-e-s in eGon100RE #1073
- Change hgv data source to use database #1086
- Change desposit ID for data_bundle download from zenodo sandbox #1110
- Use MaStR geocoding results for pv rooftop to buildings mapping workflow #1095
- Rename eMob MIT carrier names (use underscores) #1105

9.1.3 Bug Fixes

- Some dependencies have their upper versions restricted now. This is mostly due to us not yet supporting Airflow 2.0 which means that it will no longer work with certain packages, but we also won't get and upper version limit for those from Airflow because version 1.X is unlikely to to get an update. So we had to make some implicit dependencies explicit in order to give them them upper version limits. Done via PR #692 in order to fix issues #343, #556, #641 and #669.
- Heat demand data import #157
- Substation sequence #171
- Adjust names of demandregios nuts3 regions according to nuts version 2016 #201

- Delete zensus buildings, apartments and households in unpopulated cells #202
- Fix input table of electrical-demands-zensus #217
- Import heat demand raster files successively to fix import for dataset==Everything #204
- Replace wrong table name in SQL function used in substation extraction #236
- Fix osmtgmod for osm data from 2021 by updating substation in Garenfeld and set srid #241 #258
- Adjust format of voltage levels in hvmv substation #248
- Change order of osmtgmod tasks #253
- Fix missing municipalities #279
- Fix import of hydro power plants #270
- Fix path to osm-file for osmtgmod_osm_import #258
- Fix conflicting docker containers by setting a project name #289
- Update task insert-nep-data for pandas version 1.3.0 #322
- Fix versioning conflict with mv_grid_districts #340
- Set current working directory as java's temp dir when executing osmosis #344
- Fix border gas voronoi polygons which had no bus_id #362
- Add dependency from WeatherData to Vg250 #387
- Fix unnecessary columns in normal mode for inserting the gas production #390
- Add xlrd and openpyxl to installation setup #400
- Store files of OSM, zensus and VG250 in working dir #341
- Remove hard-coded slashes in file paths to ensure Windows compatibility #398
- Add missing dependency in pipeline.py #412
- Add prefix egon to MV grid district tables #349
- Bump MV grid district version no #432
- Add curl to prerequisites in the docs #440
- Replace NAN by 0 to avoid empty p_set column in DB #414
- Exchange bus 0 and bus 1 in Power-to-H2 links #458
- Fix missing cts demands for eGon2035 #511
- Add *data_bundle* to *industrial_sites* task dependencies #468
- Lift *geopandas* minimum requirement to *0.10.0* #504
- Use inbuilt *datetime* package instead of *pandas.datetime* #516
- Add missing 'sign' for CH4 and H2 loads #538
- Delete only AC loads for eTraGo in electricity_demand_etrago #535
- Filter target values by scenario name #570
- Reduce number of timesteps of hh electricity demand profiles to 8760 #593
- Fix assignemnt of heat demand profiles at German borders #585
- Change source for H2 steel tank storage to Danish Energy Agency #605

- Change carrier name from ‘pv’ to ‘solar’ in eTraGo_generators #617
- Assign “carrier” to transmission lines with no value in grid.egon_etrago_line #625
- Fix deleting from eTraGo tables #613
- Fix positions of the foreign gas buses #618
- Create and fill transfer_busses table in substation-dataset #610
- H2 steel tanks are removed again from saltcavern storage #621
- Timeseries not deleted from grid.etrago_generator_timeseries #645
- Fix function to get scaled hh profiles #674
- Change order of pypsa-eur-sec and scenario-capacities #589
- Fix gas storages capacities #676
- Distribute rural heat supply to residetntial and service demands #679
- Fix time series creation for pv rooftop #688
- Fix extraction of buildings without amenities #693
- Assign DLR capacities to every transmission line #683
- Fix solar ground mounted total installed capacity #695
- Fix twisted number error residential demand #704
- Fix industrial H2 and CH4 demand for eGon100RE scenario #687
- Clean up *“pipeline.py”* #562
- Assign timeseries data to crossborder generators ego2035 #724
- Add missing dataset dependencies in “pipeline.py” #725
- Fix assignemnt of impedances (x) to etrago tables #710
- Fix country_code attribution of two gas buses #744
- Fix voronoi assignemnt for enclaves #734
- Set lengths of non-pipeline links to 0 #741
- Change table name from `boundaries.saltstructures_inspee` to `boundaries.inspee_saltstructures` #746
- Add missing marginal costs for conventional generators in Germany #722
- Fix carrier name for solar ground mounted in scenario parameters #752
- Create rural_heat buses only for mv grid districts with heat load #708
- Solve problem while creating generators series data egon2035 #758
- Correct wrong carrier name when assigning marginal costs #766
- Use db.next_etrago_id in dsm and pv_rooftop dataset #748
- Add missing dependency to heat_etrago #771
- Fix country code of gas pipeline DE-AT #813
- Fix distribution of resistive heaters in district heating grids #783
- Fix missing reservoir and run_of_river power plants in eTraGo tables, Modify fill_etrago_gen to also group generators from eGon100RE, Use db.next_etrago_id in fill_etrago_gen #798 #776

- Fix model load timeseries in motorized individual travel #830
- Fix gas costs #847
- Add imports that have been wrongly deleted #849
- Fix final demand of heat demand timeseries #781
- Add extendable batteries only to buses at substations #852
- Move class definition for grid.egon_gas_voronoi out of etrago_setup #888
- Temporarily set upper version limit for pandas #829
- Change industrial gas load modelling #871
- Delete eMob MIT data from eTraGo tables on init #878
- Fix model id issues in DSM potentials for CTS and industry #901
- Drop isolated buses and tranformers in eHV grid #874
- Model gas turbines always as links #914
- Drop era5 weather cell table using cascade #909
- Remove drop of p_set and q_set for loads without timeserie #971
- Delete gas bus with wrong country code #958
- Overwrite capacities for conventional power plants with data from nep list #403
- Make gas grid links bidirectional #1021
- Correct gas technology costs for eGon100RE #984
- Adjust p_nom and marginal cost for OCGT in eGon2035 #863
- Mismatch of building bus_ids from cts_heat_demand_building_share and mapping table #989
- Fix zensus weather cells mapping #1031
- Fix solar rooftop in test mode #1055
- Add missing filter for scenario name in chp expansion #1015
- Fix installed capacity per individual heat pump #1058
- Add missing gas turbines abroad #1079
- Fix gas generators abroad (marginal cost and e_nom_max) #1075
- Fix gas pipelines isolated of the German grid #1081
- Fix aggregation of DSM-components #1069
- Fix URL of TYNDP scenario dataset
- Automatically generated tasks now get unique `task_id`s. Fixes issue #985 via PR #986.
- Adjust capcities of German CH4 stores #1096
- Fix faulty DSM time series #1088
- Set upper limit on commissioning date for units from MaStR dataset #1098
- Fix conversion factor for CH4 loads abroad in eGon2035 #1104
- Change structure of documentation in rtd #11126

CHAPTER

TEN

EGON.DATA

echo(*message*)

10.1 airflow

10.2 cli

Module that contains the command line app.

Why does this file exist, and why not put this in __main__?

> You might be tempted to import things from __main__ later, but that will cause problems: the code will get executed twice:
>
> - When you run *python -megon.data* python will execute `__main__.py` as a script. That means there won't be any `egon.data.__main__` in `sys.modules`.
> - When you import __main__ it will get executed again (as a module) because there's no `egon.data.__main__` in `sys.modules`.
>
> Also see (1) from http://click.pocoo.org/5/setuptools/#setuptools-integration

main()

10.3 config

datasets(*config_file=None*)

Return dataset configuration.

Parameters **config_file** (*str, optional*) – Path of the dataset configuration file in YAML format. If not supplied, a default configuration shipped with this package is used.

Returns *dict* – A nested dictionary containing the configuration as parsed from the supplied file, or the default configuration if no file was given.

paths(*pid=None*)

Obtain configuration file paths.

If no *pid* is supplied, return the location of the standard configuration file. If *pid* is the string *"current"*, the path to the configuration file containing the configuration specific to the currently running process, i.e. the configuration obtained by overriding the values from the standard configuration file with the values explicitly supplied when the currently running process was invoked, is returned. If *pid* is the string *"*"* a list of all configuration belonging

to currently running *egon-data* processes is returned. This can be used for error checking, because there should only ever be one such file.

set_numexpr_threads()
Sets maximum threads used by NumExpr

Returns *None*

settings() → dict[str, dict[str, str]]
Return a nested dictionary containing the configuration settings.

It's a nested dictionary because the top level has command names as keys and dictionaries as values where the second level dictionary has command line switches applicable to the command as keys and the supplied values as values.

So you would obtain the `--database-name` configuration setting used by the current invocation of of `egon-data` via

```
settings()["egon-data"]["--database-name"]
```

10.4 dataset_configuration

10.5 datasets

10.5.1 DSM_cts_ind

Currently, there are differences in the aggregated and individual DSM time series. These are caused by the truncation of the values at zero.

The sum of the individual time series is a more accurate value than the aggregated time series used so far and should replace it in the future. Since the deviations are relatively small, a tolerance is currently accepted in the sanity checks. See [#1120](https://github.com/openego/eGon-data/issues/1120) for updates.

class DsmPotential(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Calculate Demand-Side Management potentials and transfer to charactersitics of DSM components

DSM within this work includes the shifting of loads within the sectors of industry and CTS. Therefore, the corresponding formerly prepared demand time sereies are used. Shiftable potentials are calculated using the parametrization elaborated in Heitkoetter et. al (doi:https://doi.org/10.1016/j.adapen.2020.100001). DSM is modelled as storage-equivalent operation using the methods by Kleinhans (doi:10.48550/ARXIV.1401.4121). The potentials are transferred to characterisitcs of DSM links (minimal and maximal shiftable power per time step) and DSM stores (minimum and maximum capacity per time step). DSM buses are created to connect DSM components with the electrical network. All DSM components are added to the corresponding tables for the transmission grid level. For the distribution grids, the respective time series are exported to the corresponding tables (for the required higher spatial resolution).

Dependencies

- *CtsElectricityDemand*
- IndustrialDemandCurves
- *Osmtgmod*

Resulting tables

- *grid.egon_etrago_bus* is extended
- *grid.egon_etrago_link* is extended
- *grid.egon_etrago_link_timeseries* is extended
- *grid.egon_etrago_store* is extended
- *grid.egon_etrago_store_timeseries* is extended
- demand.egon_etrago_electricity_cts_dsm_timeseries is created and filled # noqa: E501
- demand.egon_osm_ind_load_curves_individual_dsm_timeseries is created and filled # noqa: E501
- demand.egon_demandregio_sites_ind_electricity_dsm_timeseries is created and filled # noqa: E501
- demand.egon_sites_ind_load_curves_individual_dsm_timeseries is created and filled # noqa: E501

name: str = 'DsmPotential'

version: str = '0.0.5'

class EgonDemandregioSitesIndElectricityDsmTimeseries(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

application

bus

e_max

e_min

industrial_sites_id

p_max

p_min

p_set

scn_name

target = {'schema': 'demand', 'table': 'egon_demandregio_sites_ind_electricity_dsm_timeseries'}

class EgonEtragoElectricityCtsDsmTimeseries(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

bus

e_max

e_min

p_max

p_min

p_set

scn_name

target = {'schema': 'demand', 'table': 'egon_etrago_electricity_cts_dsm_timeseries'}

class EgonOsmIndLoadCurvesIndividualDsmTimeseries(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus

e_max

e_min

osm_id

p_max

p_min

p_set

scn_name

target = {'schema': 'demand', 'table': 'egon_osm_ind_load_curves_individual_dsm_timeseries'}

class EgonSitesIndLoadCurvesIndividualDsmTimeseries(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus

e_max

e_min

p_max

p_min

p_set

scn_name

site_id

target = {'schema': 'demand', 'table': 'egon_sites_ind_load_curves_individual_dsm_timeseries'}

aggregate_components(*df_dsm_buses*, *df_dsm_links*, *df_dsm_stores*)

calc_ind_site_timeseries(*scenario*)

calculate_potentials(*s_flex*, *s_util*, *s_inc*, *s_dec*, *delta_t*, *dsm*)

Calculate DSM-potential per bus using the methods by Heitkoetter et. al.: https://doi.org/10.1016/j.adapen.2020.100001

Parameters

s_flex: float Feasability factor to account for socio-technical restrictions

s_util: float Average annual utilisation rate

s_inc: float Shiftable share of installed capacity up to which load can be increased considering technical limitations

s_dec: float Shiftable share of installed capacity up to which load can be decreased considering technical limitations

delta_t: int Maximum shift duration in hours

dsm: DataFrame List of existing buses with DSM-potential including timeseries of loads

create_dsm_components(*con*, *p_max*, *p_min*, *e_max*, *e_min*, *dsm*, *export_aggregated=True*)
Create components representing DSM. Parameters

con : Connection to database

p_max: DataFrame Timeseries identifying maximum load increase

p_min: DataFrame Timeseries identifying maximum load decrease

e_max: DataFrame Timeseries identifying maximum energy amount to be preponed

e_min: DataFrame Timeseries identifying maximum energy amount to be postponed

dsm: DataFrame List of existing buses with DSM-potential including timeseries of loads

create_table(*df*, *table*, *engine=Engine(postgresql+psycopg2://egon:***@127.0.0.1:59734/egon-data)*)
Create table

cts_data_import(*cts_cool_vent_ac_share*)
Import CTS data necessary to identify DSM-potential.

cts_share: float Share of cooling, ventilation and AC in CTS demand

data_export(*dsm_buses*, *dsm_links*, *dsm_stores*, *carrier*)
Export new components to database.

Parameters

- **dsm_buses** (*DataFrame*) – Buses representing locations of DSM-potential
- **dsm_links** (*DataFrame*) – Links connecting DSM-buses and DSM-stores
- **dsm_stores** (*DataFrame*) – Stores representing DSM-potential
- **carrier** (*str*) – Remark to be filled in column 'carrier' identifying DSM-potential

delete_dsm_entries(*carrier*)
Deletes DSM-components from database if they already exist before creating new ones.

Parameters

carrier: str Remark in column 'carrier' identifying DSM-potential

div_list(*lst: list*, *div: float*)

dsm_cts_ind(*con=Engine(postgresql+psycopg2://egon:***@127.0.0.1:59734/egon-data)*,
cts_cool_vent_ac_share=0.22, *ind_vent_cool_share=0.039*, *ind_vent_share=0.017*)
Execute methodology to create and implement components for DSM considering a) CTS per osm-area: combined potentials of cooling, ventilation and air

conditioning

b) Industry per osm-are: combined potentials of cooling and ventilation

c) Industrial Sites: potentials of ventilation in sites of

"Wirtschaftszweig" (WZ) 23

d) Industrial Sites: potentials of sites specified by subsectors

identified by Schmidt (https://zenodo.org/record/3613767#.YTsGwVtCRhG): Paper, Recycled Paper, Pulp, Cement

Modelled using the methods by Heitkoetter et. al.: https://doi.org/10.1016/j.adapen.2020.100001

Parameters

- **con** – Connection to database
- **cts_cool_vent_ac_share** (*float*) – Share of cooling, ventilation and AC in CTS demand
- **ind_vent_cool_share** (*float*) – Share of cooling and ventilation in industry demand
- **ind_vent_share** (*float*) – Share of ventilation in industry demand in sites of WZ 23

`dsm_cts_ind_individual`(*cts_cool_vent_ac_share=0.22*, *ind_vent_cool_share=0.039*, *ind_vent_share=0.017*)

Execute methodology to create and implement components for DSM considering a) CTS per osm-area: combined potentials of cooling, ventilation and air

conditioning

b) Industry per osm-are: combined potentials of cooling and ventilation

c) Industrial Sites: potentials of ventilation in sites of

"Wirtschaftszweig" (WZ) 23

d) Industrial Sites: potentials of sites specified by subsectors

identified by Schmidt (https://zenodo.org/record/3613767#.YTsGwVtCRhG): Paper, Recycled Paper, Pulp, Cement

Modelled using the methods by Heitkoetter et. al.: https://doi.org/10.1016/j.adapen.2020.100001

Parameters

- **cts_cool_vent_ac_share** (*float*) – Share of cooling, ventilation and AC in CTS demand
- **ind_vent_cool_share** (*float*) – Share of cooling and ventilation in industry demand
- **ind_vent_share** (*float*) – Share of ventilation in industry demand in sites of WZ 23

`dsm_cts_ind_processing`()

`ind_osm_data_import`(*ind_vent_cool_share*)

Import industry data per osm-area necessary to identify DSM-potential.

ind_share: float Share of considered application in industry demand

`ind_osm_data_import_individual`(*ind_vent_cool_share*)

Import industry data per osm-area necessary to identify DSM-potential.

ind_share: float Share of considered application in industry demand

`ind_sites_data_import`()

Import industry sites data necessary to identify DSM-potential.

`ind_sites_vent_data_import`(*ind_vent_share*, *wz*)

Import industry sites necessary to identify DSM-potential.

ind_vent_share: float Share of considered application in industry demand

wz: int Wirtschaftszweig to be considered within industry sites

`ind_sites_vent_data_import_individual`(*ind_vent_share*, *wz*)

Import industry sites necessary to identify DSM-potential.

ind_vent_share: float Share of considered application in industry demand

wz: int Wirtschaftszweig to be considered within industry sites

`relate_to_schmidt_sites`(*dsm*)

10.5.2 calculate_dlr

Use the concept of dynamic line rating(DLR) to calculate temporal depending capacity for HV transmission lines. Inspired mainly on Planungsgrundsaetze-2020 Available at: <https://www.transnetbw.de/files/pdf/netzentwicklung/netzplanungsgrundsaetze/UENB_PlGrS_Juli2020.pdf>

`class Calculate_dlr`(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Calculate DLR and assign values to each line in the db

Parameters

- ***No parameters required**
- ***Dependencies*** –
  - *DataBundle*
  - *Osmtgmod*
  - *WeatherData*
  - FixEhvSubnetworks
- ***Resulting tables*** –
  - *grid.egon_etrago_line_timeseries* is filled

`name: str = 'dlr'`

`version: str = '0.0.1'`

`DLR_Regions`(*weather_info_path*, *regions_shape_path*)

Calculate DLR values for the given regions

Parameters

- **weather_info_path** (*str, mandatory*) – path of the weather data downloaded from ERA5
- **regions_shape_path** (*str, mandatory*) – path to the shape file with the shape of the regions to analyze

`dlr`()

Calculate DLR and assign values to each line in the db

Parameters ***No parameters required**

10.5.3 ch4_prod

The central module containing code dealing with importing CH4 production data for eGon2035.

For eGon2035, the gas produced in Germany can be natural gas or biogas. The source productions are geolocalised potentials described as PyPSA generators. These generators are not extendable and their overall production over the year is limited directly in eTraGo by values from the Netzentwicklungsplan Gas 2020–2030 (36 TWh natural gas and 10 TWh biogas), also stored in the table *scenario.egon_scenario_parameters*.

class CH4Production(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Insert the CH4 productions into the database for eGon2035

Insert the CH4 productions into the database for eGon2035 by using the function *import_gas_generators()*.

Dependencies

- *GasAreaseGon2035*
- *GasNodesAndPipes*

Resulting tables

- *grid.egon_etrago_generator* is extended

name: str = 'CH4Production'

version: str = '0.0.7'

The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

import_gas_generators(*scn_name='eGon2035'*)

Inserts list of gas production units into the database

To insert the gas production units into the database, the following steps are followed:

- cleaning of the database table grid.egon_etrago_generator of the CH4 generators of the specific scenario (eGon2035),
- call of the functions *load_NG_generators()* and *load_biogas_generators()* that respectively return dataframes containing the natural- an bio-gas production units in Germany,
- attribution of the bus_id to which each generator is connected (call the function *assign_gas_bus_id* from *egon.data.db*),
- aggregation of the CH4 productions with same properties at the same bus. The properties that should be the same in order that different generators are aggregated are:
  - scenario
  - carrier
  - marginal cost: this parameter differentiates the natural gas generators from the biogas generators,
- addition of the missing columns: scn_name, carrier and generator_id,
- insertion of the generators into the database.

Parameters **scn_name** (*str*) – Name of the scenario.

Returns *None*

load_NG_generators(*scn_name*)
Define the fossil CH4 production units in Germany

This function reads from the SciGRID_gas dataset the fossil CH4 production units in Germany, adjusts and returns them. Natural gas production reference: SciGRID_gas dataset (datasets/gas_data/data/IGGIELGN_Production.csv downloaded in *download_SciGRID_gas_data*). For more information on this data, refer to the SciGRID_gas IGGIELGN documentation.

Parameters **scn_name** (*str*) – Name of the scenario.

Returns **CH4_generators_list** (*pandas.DataFrame*) – Dataframe containing the natural gas production units in Germany

load_biogas_generators(*scn_name*)
Define the biogas production units in Germany

This function downloads the Biogaspartner Einspeiseatlas into (datasets/gas_data/Biogaspartner_Einspeiseatlas_Deutschland_2021 reads the biogas production units in Germany data, adjusts and returns them. For more information on this data refer to the Einspeiseatlas website.

Parameters **scn_name** (*str*) – Name of the scenario

Returns **CH4_generators_list** (*pandas.DataFrame*) – Dataframe containing the biogas production units in Germany

10.5.4 ch4_storages

The central module containing all code dealing with importing gas stores

This module contains the functions to import the existing methane stores in Germany and inserting them into the database. They are modelled as PyPSA stores and are not extendable.

class CH4Storages(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Inserts the gas stores in Germany

Inserts the non extendable gas stores in Germany into the database for the scnenarios eGon2035 and eGon100RE using the function *insert_ch4_storages()*.

Dependencies

- *GasAreaseGon2035*
- *GasAreaseGon2035*
- *GasNodesAndPipes*

Resulting tables

- *grid.egon_etrago_store* is extended

name: str = 'CH4Storages'

version: str = '0.0.3'

import_ch4_grid_capacity(*scn_name*)
Defines the gas stores modelling the store capacity of the grid

Define dataframe containing the modelling of the grid storage capacity. The whole storage capacity of the grid (130000 MWh, estimation of the Bundesnetzagentur) is split uniformly between all the German gas nodes of the grid (without consideration of the capacities of the pipes). In eGon100RE, the storage capacity of the grid is split between H2 and CH4 stores, with the same share as the pipeline capacities (value calculated in the p-e-s run).

Parameters

- **scn_name** (*str*) – Name of the scenario
- **carrier** (*str*) – Name of the carrier

Returns *Gas_storages_list* – List of gas stores in Germany modelling the gas grid storage capacity

`import_installed_ch4_storages`(*scn_name*)

Defines list of CH4 stores from the SciGRID_gas data

This function reads from the SciGRID_gas dataset the existing CH4 cavern stores in Germany, adjusts and returns them. Caverns reference: SciGRID_gas dataset (datasets/gas_data/data/IGGIELGN_Storages.csv downloaded in *download_SciGRID_gas_data*). For more information on these data, refer to the SciGRID_gas IGGIELGN documentation.

Parameters **scn_name** (*str*) – Name of the scenario

Returns *Gas_storages_list* – Dataframe containing the CH4 cavern store units in Germany

`insert_ch4_storages`()

Overall function to import non extendable gas stores in Germany

This function inserts the methane stores in Germany for the scenarios eGon2035 and eGon100RE by using the function *insert_ch4_stores()* and has no return.

`insert_ch4_stores`(*scn_name*)

Inserts gas stores for specific scenario

Insert non extendable gas stores for specific scenario in Germany by executing the following steps:

- Clean the database.
- For CH4 stores, call the functions *import_installed_ch4_storages()* to get the CH4 cavern stores and *import_ch4_grid_capacity()* to get the CH4 stores modelling the storage capacity of the grid.
- Aggregate the stores attached to the same bus.
- Add the missing columns: store_id, scn_name, carrier, e_cyclic.
- Insert the stores into the database.

Parameters **scn_name** (*str*) – Name of the scenario.

Returns *None*

10.5.5 chp_etrago

The central module containing all code dealing with chp for eTraGo.

`class ChpEtrago`(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Collect data related to combined heat and power plants for the eTraGo tool

This dataset collects data for combined heat and power plants and puts it into a format that is needed for the transmission grid optimisation within the tool eTraGo. This data is then writting into the corresponding tables that are read by eTraGo.

Dependencies

- *HeatEtrago*
- *Chp*

Resulting tables

- *grid.egon_etrago_link* is extended
- *grid.egon_etrago_generator* is extended

name: str = 'ChpEtrago'

version: str = '0.0.6'

insert()

Insert combined heat and power plants into eTraGo tables.

Gas CHP plants are modeled as links to the gas grid, biomass CHP plants (only in eGon2035) are modeled as generators

Returns *None.*

insert_egon100re()

Insert combined heat and power plants into eTraGo tables for the eGon100RE scenario.

Returns *None.*

10.5.6 database

setup()

Initialize the local database used for data processing.

10.5.7 electrical_neighbours

The central module containing all code dealing with electrical neighbours

class ElectricalNeighbours(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Add lines, loads, generation and storage for electrical neighbours

This dataset creates data for modelling the considered foreign countries and writes that data into the database tables that can be read by the eTraGo tool. Neighbouring countries are modelled in a lower spatial resolution, in general one node per country is considered. Defined load timeseries as well as generatrion and storage capacities are connected to these nodes. The nodes are connected by AC and DC transmission lines with the German grid and other neighbouring countries considering the grid topology from ENTSO-E.

Dependencies

- *Tyndp*
- *PypsaEurSec*

Resulting tables

- *grid.egon_etrago_bus* is extended
- *grid.egon_etrago_link* is extended
- *grid.egon_etrago_line* is extended
- *grid.egon_etrago_load* is extended
- *grid.egon_etrago_load_timeseries* is extended
- grid.egon_etrago_storage is extended
- *grid.egon_etrago_generator* is extended

- *grid.egon_etrago_generator_timeseries* is extended
- *grid.egon_etrago_transformer* is extended

name: `str = 'ElectricalNeighbours'`

version: `str = '0.0.7'`

buses(*scenario*, *sources*, *targets*)
Insert central buses in foreign countries per scenario

Parameters

- **sources** (*dict*) – List of dataset sources
- **targets** (*dict*) – List of dataset targets

Returns **central_buses** (*geoapndas.GeoDataFrame*) – Buses in the center of foreign countries

calc_capacities()
Calculates installed capacities from TYNDP data

Returns *pandas.DataFrame* – Installed capacities per foreign node and energy carrier

central_buses_egon100(*sources*)
Returns buses in the middle of foreign countries based on eGon100RE

Parameters **sources** (*dict*) – List of sources

Returns *pandas.DataFrame* – Buses in the center of foreign countries

central_transformer(*scenario*, *sources*, *targets*, *central_buses*, *new_lines*)
Connect central foreign buses with different voltage levels

Parameters

- **sources** (*dict*) – List of dataset sources
- **targets** (*dict*) – List of dataset targets
- **central_buses** (*geopandas.GeoDataFrame*) – Buses in the center of foreign countries
- **new_lines** (*geopandas.GeoDataFrame*) – Lines that connect cross-border lines to central bus per country

Returns *None.*

choose_transformer(*s_nom*)
Select transformer and parameters from existing data in the grid model

It is assumed that transformers in the foreign countries are not limiting the electricity flow, so the capacitiy s_nom is set to the minimum sum of attached AC-lines. The electrical parameters are set according to already inserted transformers in the grid model for Germany.

Parameters **s_nom** (*float*) – Minimal sum of nominal power of lines at one side

Returns

- *int* – Selected transformer nominal power
- *float* – Selected transformer nominal impedance

cross_border_lines(*scenario*, *sources*, *targets*, *central_buses*)
Adds lines which connect border-crossing lines from osmtgmod to the central buses in the corresponding neighbouring country

Parameters

- **sources** (*dict*) – List of dataset sources
- **targets** (*dict*) – List of dataset targets
- **central_buses** (*geopandas.GeoDataFrame*) – Buses in the center of foreign countries

Returns **new_lines** (*geopandas.GeoDataFrame*) – Lines that connect cross-border lines to central bus per country

`foreign_dc_lines`(*scenario*, *sources*, *targets*, *central_buses*)
Insert DC lines to foreign countries manually

Parameters

- **sources** (*dict*) – List of dataset sources
- **targets** (*dict*) – List of dataset targets
- **central_buses** (*geopandas.GeoDataFrame*) – Buses in the center of foreign countries

Returns *None.*

`get_cross_border_buses`(*scenario*, *sources*)
Returns buses from osmTGmod which are outside of Germany.

Parameters **sources** (*dict*) – List of sources

Returns *geopandas.GeoDataFrame* – Electricity buses outside of Germany

`get_cross_border_lines`(*scenario*, *sources*)
Returns lines from osmTGmod which end or start outside of Germany.

Parameters **sources** (*dict*) – List of sources

Returns *geopandas.GeoDataFrame* – AC-lines outside of Germany

`get_foreign_bus_id`()
Calculte the etrago bus id from Nodes of TYNDP based on the geometry

Returns *pandas.Series* – List of mapped node_ids from TYNDP and etragos bus_id

`get_map_buses`()
Returns a dictonary of foreign regions which are aggregated to another

Returns *Combination of aggregated regions*

`grid`()
Insert electrical grid compoenents for neighbouring countries

Returns *None.*

`insert_generators`(*capacities*)
Insert generators for foreign countries based on TYNDP-data

Parameters **capacities** (*pandas.DataFrame*) – Installed capacities per foreign node and energy carrier

Returns *None.*

`insert_storage`(*capacities*)
Insert storage units for foreign countries based on TYNDP-data

Parameters **capacities** (*pandas.DataFrame*) – Installed capacities per foreign node and energy carrier

Returns *None.*

map_carriers_tyndp()
Map carriers from TYNDP-data to carriers used in eGon :returns: *dict* – Carrier from TYNDP and eGon

tyndp_demand()
Copy load timeseries data from TYNDP 2020. According to NEP 2021, the data for 2030 and 2040 is interpolated linearly.

Returns *None.*

tyndp_generation()
Insert data from TYNDP 2020 accordning to NEP 2021 Scenario 'Distributed Energy', linear interpolate between 2030 and 2040

Returns *None.*

10.5.8 electricity_demand_etrago

The central module containing code to merge data on electricity demand and feed this data into the corresponding etraGo tables.

class ElectricalLoadEtrago(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

demands_per_bus(*scenario*)
Sum all electricity demand curves up per bus

Parameters **scenario** (*str*) – Scenario name.

Returns *pandas.DataFrame* – Aggregated electrical demand timeseries per bus

export_to_db()
Prepare and export eTraGo-ready information of loads per bus and their time series to the database

Returns *None.*

store_national_profiles(*ind_curves_sites*, *ind_curves_osm*, *cts_curves*, *hh_curves*, *scenario*)
Store electrical load timeseries aggregated for national level as an input for pypsa-eur-sec

Parameters

- **ind_curves_sites** (*pd.DataFrame*) – Industrial load timeseries for industrial sites per bus
- **ind_curves_osm** (*pd.DataFrame*) – Industrial load timeseries for industrial osm areas per bus
- **cts_curves** (*pd.DataFrame*) – CTS load curves per bus
- **hh_curves** (*pd.DataFrame*) – Household load curves per bus
- **scenario** (*str*) – Scenario name

Returns *None.*

10.5.9 era5

Central module containing all code dealing with importing era5 weather data.

class EgonEra5Cells(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

geom

geom_point

w_id

class EgonRenewableFeedIn(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

carrier

feedin

w_id

weather_year

class WeatherData(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Download weather data from ERA5 using atlite

This dataset downloads weather data for the selected representative weather year. This is done by applying functions from the atlite-tool.The downloaded wetaher data is stored into files within the subfolder 'cutouts'.

Dependencies

- *ScenarioParameters*
- *Vg250*
- *Setup*

Resulting tables

- *supply.egon_era5_weather_cells* is created and filled
- *supply.egon_era5_renewable_feedin* is created

name: str = 'Era5'

version: str = '0.0.2'

create_tables()

download_era5()
Download weather data from era5

Returns *None.*

import_cutout(*boundary='Europe'*)
Import weather data from cutout

Returns **cutout** (*atlite.cutout.Cutout*) – Weather data stored in cutout

insert_weather_cells()
Insert weather cells from era5 into database table

Returns *None.*

10.5.10 etrago_helpers

Module for repeated bus insertion tasks

`copy_and_modify_buses`(*from_scn*, *to_scn*, *filter_dict*)
Copy buses from one scenario to a different scenario

Parameters

- **from_scn** (*str*) – Source scenario.
- **to_scn** (*str*) – Target scenario.
- **filter_dict** (*dict*) – Filter buses according the information provided in this dict.

`copy_and_modify_links`(*from_scn*, *to_scn*, *carriers*, *sector*)
Copy links from one scenario to a different one.

Parameters

- **from_scn** (*str*) – Source scenario.
- **to_scn** (*str*) – Target scenario.
- **carriers** (*list*) – List of store carriers to copy.
- **sector** (*str*) – Name of sector (e.g. `'gas'`) to get cost information from.

`copy_and_modify_stores`(*from_scn*, *to_scn*, *carriers*, *sector*)
Copy stores from one scenario to a different one.

Parameters

- **from_scn** (*str*) – Source scenario.
- **to_scn** (*str*) – Target scenario.
- **carriers** (*list*) – List of store carriers to copy.
- **sector** (*str*) – Name of sector (e.g. `'gas'`) to get cost information from.

`finalize_bus_insertion`(*bus_data*, *carrier*, *target*, *scenario='eGon2035'*)
Finalize bus insertion to etrago table

Parameters

- **bus_data** (*geopandas.GeoDataFrame*) – GeoDataFrame containing the processed bus data.
- **carrier** (*str*) – Name of the carrier.
- **target** (*dict*) – Target schema and table information.
- **scenario** (*str, optional*) – Name of the scenario The default is 'eGon2035'.

Returns **bus_data** (*geopandas.GeoDataFrame*) – GeoDataFrame containing the inserted bus data.

`initialise_bus_insertion`(*carrier*, *target*, *scenario='eGon2035'*)
Initialise bus insertion to etrago table

Parameters

- **carrier** (*str*) – Name of the carrier.
- **target** (*dict*) – Target schema and table information.
- **scenario** (*str, optional*) – Name of the scenario The default is 'eGon2035'.

Returns **gdf** (*geopandas.GeoDataFrame*) – Empty GeoDataFrame to store buses to.

10.5.11 etrago_setup

class EgonPfHvBus(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

carrier

country

geom

scn_name

type

v_mag_pu_max

v_mag_pu_min

v_mag_pu_set

v_nom

x

y

class EgonPfHvBusTimeseries(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

scn_name

v_mag_pu_set

class EgonPfHvBusmap(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus0

bus1

path_length

scn_name

version

class EgonPfHvCarrier(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

co2_emissions

color

commentary

name

nice_name

class EgonPfHvGenerator(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

build_year

bus

capital_cost

carrier

committable

control

down_time_before

e_nom_max

efficiency

generator_id

lifetime

marginal_cost

min_down_time

min_up_time

p_max_pu

p_min_pu

p_nom

p_nom_extendable

p_nom_max

p_nom_min

p_set

q_set

ramp_limit_down

ramp_limit_shut_down

ramp_limit_start_up

ramp_limit_up

scn_name

shut_down_cost

sign

start_up_cost

type

up_time_before

class EgonPfHvGeneratorTimeseries(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

generator_id

marginal_cost

p_max_pu

p_min_pu

p_set

q_set

scn_name

temp_id

class EgonPfHvLine(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

b

build_year

bus0

bus1

cables

capital_cost

carrier

g

geom

length

lifetime

line_id

num_parallel

r

s_max_pu

s_nom

s_nom_extendable

s_nom_max

s_nom_min

scn_name

terrain_factor

topo

type

v_ang_max

v_ang_min

v_nom

x

class EgonPfHvLineTimeseries(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

line_id

s_max_pu

scn_name

temp_id

class EgonPfHvLink(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

build_year

bus0

bus1

capital_cost

carrier

efficiency

geom

length

lifetime

link_id

marginal_cost

p_max_pu

p_min_pu

p_nom

p_nom_extendable

p_nom_max

p_nom_min

p_set

scn_name

terrain_factor

topo

type

class EgonPfHvLinkTimeseries(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

efficiency

link_id

marginal_cost

p_max_pu

p_min_pu

p_set

scn_name

temp_id

class EgonPfHvLoad(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus

carrier

load_id

p_set

q_set

scn_name

sign

type

class EgonPfHvLoadTimeseries(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

load_id

p_set

q_set

scn_name

temp_id

class EgonPfHvStorage(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

build_year

bus

capital_cost

carrier

control

cyclic_state_of_charge

efficiency_dispatch

efficiency_store

inflow

lifetime

marginal_cost

max_hours

p_max_pu

p_min_pu

p_nom

p_nom_extendable

p_nom_max

p_nom_min

p_set

q_set

scn_name

sign

standing_loss

state_of_charge_initial

state_of_charge_set

storage_id

type

class EgonPfHvStorageTimeseries(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

inflow

marginal_cost

p_max_pu

p_min_pu

p_set

q_set

scn_name

state_of_charge_set

storage_id

temp_id

class EgonPfHvStore(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

build_year

bus

capital_cost

carrier

e_cyclic

e_initial

e_max_pu

e_min_pu

e_nom

e_nom_extendable

e_nom_max

e_nom_min

lifetime

marginal_cost

p_set

q_set

scn_name

sign

standing_loss

store_id

type

class EgonPfHvStoreTimeseries(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

e_max_pu

e_min_pu

marginal_cost

p_set

q_set

scn_name

store_id

temp_id

class EgonPfHvTempResolution(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

resolution

start_time

temp_id

timesteps

class EgonPfHvTransformer(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

b

build_year

bus0

bus1

capital_cost

g

geom

lifetime

model

num_parallel

phase_shift

r

s_max_pu

s_nom

s_nom_extendable

s_nom_max

s_nom_min

scn_name

tap_position

tap_ratio

tap_side

topo

trafo_id

type

v_ang_max

v_ang_min

x

class EgonPfHvTransformerTimeseries(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

s_max_pu

scn_name

temp_id

trafo_id

class EtragoSetup(*dependencies*)

Bases: *egon.data.datasets.Dataset*

name: str

The name of the Dataset

version: str

The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

check_carriers()

Check if any eTraGo table has carriers not included in the carrier table.

Raises

- **ValueError if carriers that are not defined in the carriers table are** –
- **used in any eTraGo table.** –

create_tables()

Create tables for eTraGo input data. :returns: *None.*

insert_carriers()

Insert list of carriers into eTraGo table

Returns *None.*

link_geom_from_buses(*df*, *scn_name*)

Add LineString geometry accoring to geometry of buses to links

Parameters

- **df** (*pandas.DataFrame*) – List of eTraGo links with bus0 and bus1 but without topology
- **scn_name** (*str*) – Scenario name

Returns **gdf** (*geopandas.GeoDataFrame*) – List of eTraGo links with bus0 and bus1 but with topology

temp_resolution()

Insert temporal resolution for etrago

Returns *None.*

10.5.12 fill_etrago_gen

class Egon_etrago_gen(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Group generators based on Scenario, carrier and bus. Marginal costs are assigned to generators without this data. Grouped generators are sent to the egon_etrago_generator table and a timeseries is assigned to the weather dependent ones.

Dependencies

- *PowerPlants*
- *WeatherData*

Resulting tables

- :py:class:`grid.egon_etrago_generator

<egon.data.datasets.etrago_setup.EgonPfHvGenerator>` is extended * *grid.egon_etrago_generator_timeseries* is filled

name: str = 'etrago_generators'

version: str = '0.0.8'

add_marginal_costs(*power_plants*)

adjust_renew_feedin_table(*renew_feedin*, *cfg*)

consistency(*data*)

delete_previuos_gen(*cfg*, *con*, *etrago_gen_orig*, *power_plants*)

fill_etrago_gen_table(*etrago_pp2*, *etrago_gen_orig*, *cfg*, *con*)

fill_etrago_gen_time_table(*etrago_pp*, *power_plants*, *renew_feedin*, *pp_time*, *cfg*, *con*)

fill_etrago_generators()

group_power_plants(*power_plants*, *renew_feedin*, *etrago_gen_orig*, *cfg*)

load_tables(*con*, *cfg*)

numpy_nan(*data*)

power_timeser(*weather_data*)

set_timeseries(*power_plants*, *renew_feedin*)

10.5.13 fix_ehv_subnetworks

The central module containing all code dealing with fixing ehv subnetworks

class FixEhvSubnetworks(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Manually fix grid topology in the extra high voltage grid to avoid subnetworks

This dataset includes fixes for the topology of the German extra high voltage grid. The initial grid topology from openstreetmap resp. osmTGmod includes some issues, eg. because of incomplete data. Thsi dataset does not fix all those issues, but deals only with subnetworks in the extra high voltage grid that would result into problems in the grid optimisation.

Dependencies

- *Osmtgmod*

Resulting tables

- *grid.egon_etrago_bus* is updated
- *grid.egon_etrago_line* is updated
- *grid.egon_etrago_transformer* is updated

name: str = 'FixEhvSubnetworks'

version: str = '0.0.2'

add_bus(*x*, *y*, *v_nom*, *scn_name*)

add_line(*x0*, *y0*, *x1*, *y1*, *v_nom*, *scn_name*, *cables*)

add_trafo(*x*, *y*, *v_nom0*, *v_nom1*, *scn_name*, *n=1*)

drop_bus(*x*, *y*, *v_nom*, *scn_name*)

drop_line(*x0*, *y0*, *x1*, *y1*, *v_nom*, *scn_name*)

drop_trafo(*x*, *y*, *v_nom0*, *v_nom1*, *scn_name*)

fix_subnetworks(*scn_name*)

run()

select_bus_id(*x*, *y*, *v_nom*, *scn_name*, *carrier*)

10.5.14 gas_areas

The central module containing code to create CH4 and H2 voronoi polygons

class EgonPfHvGasVoronoi(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table grid.egon_gas_voronoi

bus_id

Bus of the corresponding area

carrier

Gas carrier of the voronoi area (“CH4”, “H2_grid” or “H2_saltcavern”)

geom
Geometry of the corresponding area

scn_name
Name of the scenario

class GasAreaseGon100RE(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Create the gas voronoi table and the gas voronoi areas for eGon100RE

Dependencies

- *EtragoSetup*
- *HydrogenBusEtrago*
- *HydrogenGridEtrago*
- *Vg250*
- *GasNodesAndPipes*
- *GasAreaseGon2035*

Resulting tables

- *EgonPfHvGasVoronoi*

name: str = 'GasAreaseGon100RE'

version: str = '0.0.1'

class GasAreaseGon2035(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Create the gas voronoi table and the gas voronoi areas for eGon2035

Dependencies

- *EtragoSetup*
- *HydrogenBusEtrago*
- *Vg250*
- *GasNodesAndPipes*

Resulting tables

- *EgonPfHvGasVoronoi*

name: str = 'GasAreaseGon2035'

version: str = '0.0.2'

create_gas_voronoi_table()
Create gas voronoi table

create_voronoi(*scn_name*, *carrier*)
Create voronoi polygons for specified carrier in specified scenario.

Parameters

- **scn_name** (*str*) – Name of the scenario
- **carrier** (*str*) – Name of the carrier

voronoi_egon100RE()
Create voronoi polygons for all gas carriers in eGon100RE scenario

voronoi_egon2035()
Create voronoi polygons for all gas carriers in eGon2035 scenario

10.5.15 gas_grid

The module contains code used to insert the methane grid into the database

The central module contains all code dealing with the import of data from SciGRID_gas (IGGIELGN dataset) and inserting the CH4 buses and links into the database for the scenarios eGon2035 and eGon100RE.

The SciGRID_gas data downloaded with *download_SciGRID_gas_data()* into the folder ./datasets/gas_data/data is also used by other modules.

In this module, only the IGGIELGN_Nodes and IGGIELGN_PipeSegments csv files are used in the function *insert_gas_data()* that inserts the CH4 buses and links, which for the case of gas represent pipelines, into the database.

class GasNodesAndPipes(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Insert the CH4 buses and links into the database.

Insert the CH4 buses and links, which for the case of gas represent pipelines, into the database for the scenarios eGon2035 and eGon100RE with the functions *insert_gas_data()* and *insert_gas_data_eGon100RE()*.

Dependencies

- *DataBundle*
- *ElectricalNeighbours*
- *Osmtgmod*
- *ScenarioParameters*
- *EtragoSetup* (more specifically the *create_tables* task)

Resulting tables

- *grid.egon_etrago_bus* is extended
- *grid.egon_etrago_link* is extended

name: str = 'GasNodesAndPipes'

version: str = '0.0.9'

ch4_nodes_number_G(*gas_nodes_list*)
Return the number of CH4 buses in Germany

Parameters **gas_nodes_list** (*pandas.DataFrame*) – Dataframe containing the gas nodes in Europe

Returns **N_ch4_nodes_G** (*int*) – Number of CH4 buses in Germany

define_gas_buses_abroad(*scn_name='eGon2035'*)
Define central CH4 buses in foreign countries for eGon2035

For the scenario eGon2035, define central CH4 buses in foreign countries. The considered foreign countries are the direct neighbouring countries, with the addition of Russia that is considered as a source of fossil CH4. Therefore, the following steps are executed:

- Definition of the foreign buses with the function *central_buses_egon100* from the module *electrical_neighbours*
- Removal of the superfluous buses in order to have only one bus in each neighbouring country
- Removal of the irrelevant columns
- Addition of the missing information: scn_name and carrier
- Attribution of an id to each bus

Parameters **scn_name** (*str*) – Name of the scenario

Returns **gdf_abroad_buses** (*pandas.DataFrame*) – Dataframe containing the gas buses in the neighbouring countries and one in the center of Germany in test mode

`define_gas_nodes_list()`

Define list of CH4 buses from SciGRID_gas IGGIELGN data

The CH4 nodes are modelled as buses. Therefore the SciGRID_gas nodes are read from the IGGIELGN_Nodes csv file previously downloaded in the function *download_SciGRID_gas_data()*, corrected (erroneous country), and returned in a dataframe.

Returns **gas_nodes_list** (*pandas.DataFrame*) – Dataframe containing the gas nodes in Europe

`define_gas_pipeline_list(gas_nodes_list, abroad_gas_nodes_list, scn_name='eGon2035')`

Define gas pipelines in Germany from SciGRID_gas IGGIELGN data

The gas pipelines, modelled as PyPSA links are read from the IGGIELGN_PipeSegments csv file previously downloded in the function *download_SciGRID_gas_data()*.

The capacities of the pipelines are determined by the correspondance table given by the parameters for the classification of gas pipelines in Electricity, heat, and gas sector data for modeling the German system related to the pipeline diameter given in the SciGRID_gas dataset.

The manual corrections allow to:

- Delete gas pipelines disconnected of the rest of the gas grid
- Connect one pipeline (also connected to Norway) disconnected of the rest of the gas grid
- Correct countries of some erroneous pipelines

Parameters

- **gas_nodes_list** (*dataframe*) – Dataframe containing the gas nodes in Europe
- **abroad_gas_nodes_list** (*dataframe*) – Dataframe containing the gas buses in the neighbouring countries and one in the center of Germany in test mode
- **scn_name** (*str*) – Name of the scenario

Returns **gas_pipelines_list** (*pandas.DataFrame*) – Dataframe containing the gas pipelines in Germany

`download_SciGRID_gas_data()`

Download SciGRID_gas IGGIELGN data from Zenodo

The following data for CH4 is downloaded into the folder ./datasets/gas_data/data:

- Buses (file IGGIELGN_Nodes.csv),
- Pipelines (file IGGIELGN_PipeSegments.csv),
- Productions (file IGGIELGN_Productions.csv),

- Storages (file IGGIELGN_Storages.csv),
- LNG terminals (file IGGIELGN_LNGs.csv).

For more information on this data refer, to the SciGRID_gas IGGIELGN documentation.

Returns *None*

`insert_CH4_nodes_list`(*gas_nodes_list*)

Insert list of German CH4 nodes into the database for eGon2035

Insert the list of German CH4 nodes into the database by executing the following steps:

- Receive the buses as parameter (from SciGRID_gas IGGIELGN data)
- Add the missing information: scn_name and carrier
- Clean the database table grid.egon_etrago_bus of the CH4 buses of the specific scenario (eGon2035) in Germany
- Insert the buses in the table grid.egon_etrago_bus

Parameters **gas_nodes_list** (*pandas.DataFrame*) – Dataframe containing the gas nodes in Europe

Returns *None*

`insert_gas_buses_abroad`(*scn_name='eGon2035'*)

Insert CH4 buses in neighbouring countries into database for eGon2035

- Definition of the CH4 buses abroad with the function *define_gas_buses_abroad()*
- Cleaning of the database table grid.egon_etrago_bus of the foreign CH4 buses of the specific scenario (eGon2035)
- Insertion of the neighbouring buses into the table grid.egon_etrago_bus.

Parameters **scn_name** (*str*) – Name of the scenario

Returns **gdf_abroad_buses** (*dataframe*) – Dataframe containing the CH4 buses in the neighbouring countries and one in the center of Germany in test mode

`insert_gas_data`()

Function for importing methane data for eGon2035

This function imports the methane data (buses and pipelines) for eGon2035, by executing the following steps:

- Download the SciGRID_gas datasets with the function *download_SciGRID_gas_data()*
- Define CH4 buses with the function *define_gas_nodes_list()*
- Insert the CH4 buses in Germany into the database with the function *insert_CH4_nodes_list()*
- Insert the CH4 buses abroad into the database with the function *insert_gas_buses_abroad()*
- Insert the CH4 links representing the CH4 pipeline into the database with the function *insert_gas_pipeline_list()*
- Remove the isolated CH4 buses directly from the database using the function *remove_isolated_gas_buses()*

Returns *None*

insert_gas_data_eGon100RE()
Function for importing methane data for eGon100RE

This function imports the methane data (buses and pipelines) for eGon100RE, by copying the CH4 buses from the eGon2035 scenario using the function *copy_and_modify_buses* from the module *etrago_helpers*. The methane pipelines are also copied and their capacities are adapted: one share of the methane grid is retroffited into an hydrogen grid, so the methane pipelines nominal capacities are reduced from this share (calculated in the pyspa-eur-sec run).

Returns *None*

insert_gas_pipeline_list(*gas_pipelines_list*, *scn_name='eGon2035'*)
Insert list of gas pipelines into the database

Receive as argument a list of gas pipelines and insert them into the database after cleaning it.

Parameters

- **gas_pipelines_list** (*pandas.DataFrame*) – Dataframe containing the gas pipelines in Germany
- **scn_name** (*str*) – Name of the scenario

Returns *None*

remove_isolated_gas_buses()
Delete CH4 buses which are disconnected of the CH4 grid for the eGon2035 scenario

Returns *None*

10.5.16 generate_voronoi

The central module containing code to create CH4 and H2 voronoi polygones

get_voronoi_geodataframe(*buses*, *boundary*)
Create voronoi polygons for the passed buses within the boundaries.

Parameters

- **buses** (*geopandas.GeoDataFrame*) – Buses to create the voronois for.
- **boundary** (*Multipolygon, Polygon*) – Bounding box for the voronoi generation.

Returns **gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containting the bus_ids and the respective voronoi polygons.

10.5.17 heat_demand_europe

Central module containing all code downloading hotmaps heat demand data.

The 2050 national heat demand of the Hotmaps current policy scenario for buildings are used in the eGon100RE scenario for assumptions on national heating demands in European countries, but not for Germany. The data are downloaded to be used in the PyPSA-Eur-Sec scenario generator (forked into open_ego).

class HeatDemandEurope(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Downloads annual heat demands for European countries from hotmaps

This dataset downloads annual heat demands for all European countries for the year 2050 from hotmaps and stores the results into files. These are later used by pypsa-eur-sec.

Dependencies

- *Setup*

name: str = 'heat-demands-europe'

version: str = 'scen_current_building_demand.csv_hotmaps.0.1'

download()

Download Hotmaps current policy scenario for building heat demands.

The downloaded data contain residential and non-residential-sector national heat demands for different years.

Parameters None

Returns *None*

10.5.18 industrial_gas_demand

The central module containing code dealing with gas industrial demand

In this module, the functions to import the industrial hydrogen and methane demands from the opendata.ffe database and to insert them into the database after modification are to be found.

class IndustrialGasDemand(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Download the industrial gas demands from the opendata.ffe database

Data is downloaded to the folder ./datasets/gas_data/demand using the function *download_industrial_gas_demand()* and no dataset is resulting.

Dependencies

- *ScenarioParameters*

name: str = 'IndustrialGasDemand'

version: str = '0.0.4'

class IndustrialGasDemandeGon100RE(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Insert the hourly resolved industrial gas demands into the database for eGon100RE

Insert the industrial methane and hydrogen demands and their associated time series for the scenario eGon100RE by executing the function *insert_industrial_gas_demand_egon100RE()*.

Dependencies

- *GasAreaseGon100RE*
- *GasNodesAndPipes*
- *HydrogenBusEtrago*
- *IndustrialGasDemand*

Resulting tables

- *grid.egon_etrago_load* is extended
- *grid.egon_etrago_load_timeseries* is extended

name: str = 'IndustrialGasDemandeGon100RE'

version: str = '0.0.3'

class IndustrialGasDemandeGon2035(*dependencies*)
Bases: egon.data.datasets.Dataset

Insert the hourly resolved industrial gas demands into the database for eGon2035

Insert the industrial methane and hydrogen demands and their associated time series for the scenario eGon2035 by executing the function *insert_industrial_gas_demand_egon2035()*.

Dependencies

- *GasAreaseGon2035*
- *GasNodesAndPipes*
- *HydrogenBusEtrago*
- *IndustrialGasDemand*

Resulting tables

- *grid.egon_etrago_load* is extended
- *grid.egon_etrago_load_timeseries* is extended

name: str = 'IndustrialGasDemandeGon2035'

version: str = '0.0.3'

delete_old_entries(*scn_name*)
Delete CH4 and H2 loads and load time series for the specified scenario

Parameters **scn_name** (*str*) – Name of the scenario.

Returns *None*

download_industrial_gas_demand()
Download the industrial gas demand data from opendata.ffe database

The industrial demands for hydrogen and methane are downloaded in the folder ./datasets/gas_data/demand These loads are hourly and NUTS3-level resolved. For more information on these data, refer to the Extremos project documentation.

Returns *None*

insert_industrial_gas_demand_egon100RE()
Insert industrial gas demands into the database for eGon100RE

Insert the industrial CH4 and H2 demands and their associated time series into the database for the eGon100RE scenario. The data, previously downloaded in *download_industrial_gas_demand()* are adapted by executing the following steps:

- Clean the database with the function *delete_old_entries()*
- Read and prepare the CH4 and the H2 industrial demands and their associated time series in Germany with the function *read_and_process_demand()*
- Identify and adjust the total industrial CH4 and H2 loads for Germany generated by PyPSA-Eur-Sec
  - For CH4, the time series used is the one from H2, because the industrial CH4 demand in the opendata.ffe database is 0
  - In test mode, the total values are obtained by evaluating the share of H2 demand in the test region (NUTS1: DEF, Schleswig-Holstein) with respect to the H2 demand in full Germany model (NUTS0: DE). This task has been outsourced to save processing cost.
- Aggregate the demands with the same properties at the same gas bus

- Insert the loads into the database by executing *insert_new_entries()*
- Insert the time series associated to the loads into the database by executing *insert_industrial_gas_demand_time_series()*

Returns *None*

insert_industrial_gas_demand_egon2035()
Insert industrial gas demands into the database for eGon2035

Insert the industrial CH4 and H2 demands and their associated time series into the database for the eGon2035 scenario. The data previously downloaded in *download_industrial_gas_demand()* is adjusted by executing the following steps:

- Clean the database with the function *delete_old_entries()*
- Read and prepare the CH4 and the H2 industrial demands and their associated time series in Germany with the function *read_and_process_demand()*
- Aggregate the demands with the same properties at the same gas bus
- Insert the loads into the database by executing *insert_new_entries()*
- Insert the time series associated to the loads into the database by executing *insert_industrial_gas_demand_time_series()*

Returns *None*

insert_industrial_gas_demand_time_series(*egon_etrago_load_gas*)
Insert list of industrial gas demand time series (one per NUTS3 region)

These loads are hourly and on NUTS3 level resolved.

Parameters **industrial_gas_demand** (*pandas.DataFrame*) – Dataframe containing the loads that have been inserted into the database and whose time series will be inserted into the database.

Returns *None*

insert_new_entries(*industrial_gas_demand*, *scn_name*)
Insert industrial gas loads into the database

This function prepares and imports the industrial gas loads by executing the following steps:

- Attribution of an id to each load in the list received as parameter
- Deletion of the column containing the time series (they will be inserted in another table (grid.egon_etrago_load_timeseries) in the *insert_industrial_gas_demand_time_series()*)
- Insertion of the loads into the database
- Return of the dataframe still containing the time series columns

Parameters

- **industrial_gas_demand** (*pandas.DataFrame*) – Load data to insert (containing the time series)
- **scn_name** (*str*) – Name of the scenario.

Returns **industrial_gas_demand** (*pandas.DataFrame*) – Dataframe containing the loads that have been inserted in the database with their time series

read_and_process_demand(*scn_name='eGon2035'*, *carrier=None*, *grid_carrier=None*)
Assign the industrial gas demand in Germany to buses

This function prepares and returns the industrial gas demand time series for CH4 or H2 and for a specific scenario by executing the following steps:

- Read the industrial demand time series in Germany with the function *read_industrial_demand()*
- Attribute the bus_id to which each load and it associated time series is associated by calling the function *assign_gas_bus_id* from *egon.data.db*
- Adjust the columns: add "carrier" and remove useless ones

Parameters

- **scn_name** (*str*) – Name of the scenario
- **carrier** (*str*) – Name of the carrier, the demand should hold
- **grid_carrier** (*str*) – Carrier name of the buses, the demand should be assigned to

Returns **industrial_demand** (*pandas.DataFrame*) – Dataframe containing the industrial demand in Germany

read_industrial_demand(*scn_name*, *carrier*)
Read the industrial gas demand data in Germany

This function reads the methane or hydrogen industrial demand time series previously downloaded in *download_industrial_gas_demand()* for the scenarios eGon2035 or eGon100RE.

Parameters

- **scn_name** (*str*) – Name of the scenario
- **carrier** (*str*) – Name of the gas carrier

Returns **df** (*pandas.DataFrame*) – Dataframe containing the industrial gas demand time series

10.5.19 mastr

Download Marktstammdatenregister (MaStR) from Zenodo.

download_mastr_data()
Download MaStR data from Zenodo.

class mastr_data_setup(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Download Marktstammdatenregister (MaStR) from Zenodo.

Dependencies

- *Setup*

The downloaded data incorporates two different datasets:

Dump 2021-05-03

- Source: https://sandbox.zenodo.org/record/808086
- Used technologies: PV plants, wind turbines, biomass, hydro plants, combustion, nuclear, gsgk, storage
- Data is further processed in the *PowerPlants* dataset

Dump 2022-11-17

- Source: https://sandbox.zenodo.org/record/1132839
- Used technologies: PV plants, wind turbines, biomass, hydro plants
- Data is further processed in module *mastr* and *PowerPlants*

See documentation section mastr-ref for more information.

name: str = 'MastrData'

tasks: *egon.data.datasets.Tasks* = (<function download_mastr_data>,)

version: str = '0.0.1'

10.5.20 mv_grid_districts

The module containing all code to generate MV grid district polygons.

Medium-voltage grid districts describe the area supplied by one MV grid and are defined by one polygon that represents the supply area.

class HvmvSubstPerMunicipality(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of temporary table grid.hvmv_subst_per_municipality.

ags_0

area_ha

bem

bez

count_hole

gen

geometry

id

is_hole

nuts

old_id

path

rs_0

subst_count

class MvGridDistricts(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table grid.egon_mv_grid_district.

area

bus_id

geom

class MvGridDistrictsDissolved(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of temporary table grid.egon_mv_grid_district_dissolved.

area

bus_id

geom

id

class Vg250GemClean(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table boundaries.vg250_gem_clean.

ags_0

area_ha

bem

bez

count_hole

gen

geometry

id

is_hole

nuts

old_id

path

rs_0

class VoronoiMunicipalityCuts(**kwargs)
Bases: egon.data.datasets.mv_grid_districts.VoronoiMunicipalityCutsBase, sqlalchemy.ext.declarative.api.Base

Class definition of temporary table grid.voronoi_municipality_cuts.

ags_0

bus_id

geom

geom_sub

id

municipality_id

subst_count

voronoi_id

class VoronoiMunicipalityCutsAssigned(**kwargs)
Bases: egon.data.datasets.mv_grid_districts.VoronoiMunicipalityCutsBase, sqlalchemy.ext.declarative.api.Base

Class definition of temporary table grid.voronoi_municipality_cuts_assigned.

ags_0

bus_id

geom

geom_sub

id

municipality_id

subst_count

temp_id

voronoi_id

class VoronoiMunicipalityCutsBase

Bases: `object`

ags_0 = Column(None, String(), table=None)

bus_id = Column(None, Integer(), table=None)

geom = Column(None, Geometry(geometry_type='POLYGON', srid=3035), table=None)

geom_sub = Column(None, Geometry(geometry_type='POINT', srid=3035), table=None)

municipality_id = Column(None, Integer(), table=None)

subst_count = Column(None, Integer(), table=None)

voronoi_id = Column(None, Integer(), table=None)

assign_substation_municipality_fragments(*with_substation*, *without_substation*, *strategy*, *session*)

Assign bus_id from next neighboring polygon to municipality fragment

For parts municipalities without a substation inside their polygon the next municipality polygon part is found and assigned.

Resulting data including information about the assigned substation is saved to *VoronoiMunicipalityCutsAssigned*.

Parameters

- **with_substation** (*SQLAlchemy subquery*) – Polygons that have a substation inside or are assigned to a substation
- **without_substation** (*SQLAlchemy subquery*) – Subquery that includes polygons without a substation
- **strategy** (*str*) – Either
  - "touches": Only polygons that touch another polygon from *with_substation* are considered
  - "within": Only polygons within a radius of 100 km of polygons without substation are considered for assignment
- **session** (*SQLAlchemy session*) – SQLAlchemy session object

Notes

The function *nearest_polygon_with_substation()* is very similar, but different in detail.

define_mv_grid_districts()
Define spatial extent of MV grid districts.

The process of identifying the boundary of medium-voltage grid districts is organized in three steps:

1. *substations_in_municipalities()*: The number of substations

   located inside each municipality is calculated.

2. *split_multi_substation_municipalities()*: The municipalities with

   >1 substation inside are split by Voronoi polygons around substations.

3. *merge_polygons_to_grid_district()*: All polygons are merged such

   that one polygon has exactly one single substation inside.

Finally, intermediate tables used for storing data temporarily are deleted.

merge_polygons_to_grid_district()
Merge municipality polygon (parts) to MV grid districts.

Polygons of municipalities and cut parts of such polygons are merged to a single grid district per one HV-MV substation. Prior determined assignment of cut polygons parts is used as well as proximity of entire municipality polygons to polygons with a substation inside.

- Step 1: Merge municipality parts that are assigned to the same substation.
- Step 2: Insert municipality polygons with exactly one substation.
- Step 3: Assign municipality polygons without a substation and insert to table.
- Step 4: Merge MV grid district parts.

Data is written to table grid.egon_mv_grid_district and to temporary table grid.egon_mv_grid_district_dissolved.

class mv_grid_districts_setup(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Sets up medium-voltage grid districts that describe the area supplied by one MV grid.

See documentation section mv-grid-districts for more information.

Dependencies

- *SubstationVoronoi*

Resulting tables

- *grid.egon_mv_grid_district* is created and filled
- *boundaries.vg250_gem_clean* is created and filled

name: str = 'MvGridDistricts'

version: str = '0.0.2'

nearest_polygon_with_substation(*with_substation*, *without_substation*, *strategy*, *session*)
Assign next neighboring polygon.

For municipalities without a substation inside their polygon the next MV grid district (part) polygon is found and assigned.

Resulting data including information about the assigned substation is saved to *MvGridDistrictsDissolved*.

Parameters

- **with_substation** (*SQLAlchemy subquery*) – Polygons that have a substation inside or are assigned to a substation
- **without_substation** (*SQLAlchemy subquery*) – Subquery that includes polygons without a substation
- **strategy** (*str*) – Either
  - "touches": Only polygons that touch another polygon from *with_substation* are considered
  - "within": Only polygons within a radius of 100 km of polygons without substation are considered for assignment
- **session** (*SQLAlchemy session*) – SQLAlchemy session object

Returns *list* – IDs of polygons that were already assigned to a polygon with a substation.

split_multi_substation_municipalities()
Split municipalities that have more than one substation.

Municipalities that contain more than one HV-MV substation in their polygon are cut by HV-MV voronoi polygons. Resulting fragments are then assigned to the next neighboring polygon that has a substation.

In detail, the following steps are performed:

- Step 1: Cut municipalities with voronoi polygons.
- Step 2: Determine number of substations inside cut polygons.
- Step 3: Separate cut polygons with exactly one substation inside.
- Step 4: Assign polygon without a substation to next neighboring polygon with a substation.
- Step 5: Assign remaining polygons that are non-touching.

Data is written to temporary tables grid.voronoi_municipality_cuts and grid.voronoi_municipality_cuts_assigned.

substations_in_municipalities()
Create a table that counts number of HV-MV substations in each MV grid.

Counting is performed in two steps:

1. HV-MV substations are spatially joined on municipalities, grouped by municipality and number of substations counted.
2. Because (1) works only for number of substations >0, all municipalities not containing a substation, are added.

Data is written to temporary table grid.hvmv_subst_per_municipality.

10.5.21 renewable_feedin

Central module containing all code dealing with processing era5 weather data.

class MapZensusWeatherCell(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

w_id

zensus_population_id

class RenewableFeedin(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Calculate possible feedin time series for renewable energy generators

This dataset calculates possible feedin timeseries for fluctuation renewable generators and coefficient of performance time series for heat pumps. Relevant input is the downloaded weather data. Parameters for the time series calcultaion are also defined by representative types of pv plants and wind turbines that are selected within this dataset. The resulting profiles are stored in the database.

Dependencies

- *WeatherData*
- *Vg250*
- *ZensusVg250*

Resulting tables

- *supply.egon_era5_renewable_feedin* is filled

name: str = 'RenewableFeedin'

version: str = '0.0.7'

federal_states_per_weather_cell()
Assings a federal state to each weather cell in Germany.

Sets the federal state to the weather celss using the centroid. Weather cells at the borders whoes centroid is not inside Germany are assinged to the closest federal state.

Returns *GeoPandas.GeoDataFrame* – Index, points and federal state of weather cells inside Germany

feedin_per_turbine()
Calculate feedin timeseries per turbine type and weather cell

Returns **gdf** (*GeoPandas.GeoDataFrame*) – Feed-in timeseries per turbine type and weather cell

heat_pump_cop()
Calculate coefficient of performance for heat pumps according to T. Brown et al: "Synergies of sector coupling and transmission reinforcement in a cost-optimised, highlyrenewable European energy system", 2018, p. 8

Returns *None.*

insert_feedin(*data*, *carrier*, *weather_year*)
Insert feedin data into database

Parameters

- **data** (*xarray.core.dataarray.DataArray*) – Feedin timeseries data
- **carrier** (*str*) – Name of energy carrier
- **weather_year** (*int*) – Selected weather year

Returns *None.*

mapping_zensus_weather()
Perform mapping between era5 weather cell and zensus grid

offshore_weather_cells(*geom_column='geom'*)
Get weather cells which intersect with Germany

Returns *GeoPandas.GeoDataFrame* – Index and points of weather cells inside Germany

pv()
Insert feed-in timeseries for pv plants to database

Returns *None.*

solar_thermal()
Insert feed-in timeseries for pv plants to database

Returns *None.*

turbine_per_weather_cell()
Assign wind onshore turbine types to weather cells

Returns **weather_cells** (*GeoPandas.GeoDataFrame*) – Weather cells in Germany including turbine type

weather_cells_in_germany(*geom_column='geom'*)
Get weather cells which intersect with Germany

Returns *GeoPandas.GeoDataFrame* – Index and points of weather cells inside Germany

wind()
Insert feed-in timeseries for wind onshore turbines to database

Returns *None.*

wind_offshore()
Insert feed-in timeseries for wind offshore turbines to database

Returns *None.*

10.5.22 sanity_checks

This module does sanity checks for both the eGon2035 and the eGon100RE scenario separately where a percentage error is given to showcase difference in output and input values. Please note that there are missing input technologies in the supply tables. Authors: @ALonso, @dana, @nailend, @nesnoj, @khelfen

class SanityChecks(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str = 'SanityChecks'

version: str = '0.0.8'

cts_electricity_demand_share(*rtol=1e-05*)
Sanity check for dataset electricity_demand_timeseries : CtsBuildings

Check sum of aggregated cts electricity demand share which equals to one for every substation as the substation profile is linearly disaggregated to all buildings.

cts_heat_demand_share(*rtol=1e-05*)
Sanity check for dataset electricity_demand_timeseries : CtsBuildings

Check sum of aggregated cts heat demand share which equals to one for every substation as the substation profile is linearly disaggregated to all buildings.

etrago_eGon2035_electricity()
Execute basic sanity checks.

Returns print statements as sanity checks for the electricity sector in the eGon2035 scenario.

Parameters **None**

Returns *None*

etrago_eGon2035_gas_DE()
Execute basic sanity checks for the gas sector in eGon2035

Returns print statements as sanity checks for the gas sector in the eGon2035 scenario for the following components in Germany:

- Buses: with the function *sanity_check_gas_buses()*
- Loads: for the carriers 'CH4_for_industry' and 'H2_for_industry' the deviation is calculated between the sum of the loads in the database and the sum the loads in the sources document (opendata.ffe database)
- Generators: the deviation is calculated between the sums of the nominal powers of the gas generators in the database and of the ones in the sources document (Biogaspartner Einspeiseatlas Deutschland from the dena and Productions from the SciGRID_gas data)
- Stores: deviations for stores with following carriers are calculated:
  - 'CH4': with the function *sanity_check_CH4_stores()*
  - 'H2_underground': with the function *sanity_check_H2_saltcavern_stores()*
- One-port components (loads, generators, stores): verification that they are all connected to a bus present in the data base with the function *sanity_check_gas_one_port()*
- **Links: verification:**
  - that the gas links are all connected to buses present in the data base with the function *sanity_check_gas_links()*
  - of the capacity of the gas grid with the function *sanity_check_CH4_grid()*

etrago_eGon2035_gas_abroad()
Execute basic sanity checks for the gas sector in eGon2035 abroad

Returns print statements as sanity checks for the gas sector in the eGon2035 scenario for the following components in Germany:

- Buses
- Loads: for the carriers 'CH4' and 'H2_for_industry' the deviation is calculated between the sum of the loads in the database and the sum in the sources document (TYNDP)
- Generators: the deviation is calculated between the sums of the nominal powers of the methane generators abroad in the database and of the ones in the sources document (TYNDP)
- Stores: the deviation for methane stores abroad is calculated between the sum of the capacities in the data base and the one of the source document (SciGRID_gas data)
- Links: verification of the capacity of the crossbordering gas grid pipelines.

etrago_eGon2035_heat()
Execute basic sanity checks.

Returns print statements as sanity checks for the heat sector in the eGon2035 scenario.

Parameters None

Returns *None*

residential_electricity_annual_sum(*rtol=1e-05*)
Sanity check for dataset electricity_demand_timeseries : Demand_Building_Assignment

Aggregate the annual demand of all census cells at NUTS3 to compare with initial scaling parameters from DemandRegio.

residential_electricity_hh_refinement(*rtol=1e-05*)
Sanity check for dataset electricity_demand_timeseries : Household Demands

Check sum of aggregated household types after refinement method was applied and compare it to the original census values.

sanity_check_CH4_grid(*scn*)
Execute sanity checks for the gas grid capacity in Germany

Returns print statements as sanity checks for the CH4 links (pipelines) in Germany. The deviation is calculated between the sum of the power (p_nom) of all the CH4 pipelines in Germany for one scenario in the database and the sum of the powers of the imported pipelines. In eGon100RE, the sum is reduced by the share of the grid that is allocated to hydrogen (share calculated by PyPSA-eur-sec). This test works also in test mode.

Parameters **scn_name** (*str*) – Name of the scenario

Returns **scn_name** (*float*) – Sum of the power (p_nom) of all the pipelines in Germany

sanity_check_CH4_stores(*scn*)
Execute sanity checks for the CH4 stores in Germany

Returns print statements as sanity checks for the CH4 stores capacity in Germany. The deviation is calculated between:

- the sum of the capacities of the stores with carrier 'CH4' in the database (for one scenario) and
- **the sum of:**
  - the capacity the gas grid allocated to CH4 (total capacity in eGon2035 and capacity reduced the share of the grid allocated to H2 in eGon100RE)
  - the total capacity of the CH4 stores in Germany (source: GIE)

Parameters **scn_name** (*str*) – Name of the scenario

sanity_check_H2_saltcavern_stores(*scn*)
Execute sanity checks for the H2 saltcavern stores in Germany

Returns print as sanity checks for the H2 saltcavern potential storage capacity in Germany. The deviation is calculated between:

- the sum of the of the H2 saltcavern potential storage capacity (e_nom_max) in the database and
- the sum of the H2 saltcavern potential storage capacity assumed to be the ratio of the areas of 500 m radius around substations in each german federal state and the estimated total hydrogen storage potential of the corresponding federal state (data from InSpEE-DS report).

This test works also in test mode.

Parameters **scn_name** (*str*) – Name of the scenario

sanity_check_gas_buses(*scn*)
Execute sanity checks for the gas buses in Germany

Returns print statements as sanity checks for the CH4, H2_grid and H2_saltcavern buses.

- For all of them, it is checked if they are not isolated.
- For the grid buses, the deviation is calculated between the number of gas grid buses in the database and the original Scigrid_gas number of gas buses in Germany.

Parameters **scn_name** (*str*) – Name of the scenario

sanity_check_gas_links(*scn*)
Check connections of gas links

Verify that gas links are all connected to buses present in the data base. Return print statements if this is not the case. This sanity check is not specific to Germany, it also includes the neighbouring countries.

Parameters **scn_name** (*str*) – Name of the scenario

sanity_check_gas_one_port(*scn*)
Check connections of gas one-port components

Verify that gas one-port component (loads, generators, stores) are all connected to a bus (of the right carrier) present in the data base. Return print statements if this is not the case. These sanity checks are not specific to Germany, they also include the neighbouring countries.

Parameters **scn_name** (*str*) – Name of the scenario

sanitycheck_dsm()

sanitycheck_emobility_mit()
Execute sanity checks for eMobility: motorized individual travel

Checks data integrity for eGon2035, eGon2035_lowflex and eGon100RE scenario using assertions:

1. Allocated EV numbers and EVs allocated to grid districts
2. Trip data (original inout data from simBEV)
3. Model data in eTraGo PF tables (grid.egon_etrago_*)

Parameters **None**

Returns *None*

sanitycheck_home_batteries()

sanitycheck_pv_rooftop_buildings()

10.5.23 scenario_capacities

The central module containing all code dealing with importing data from Netzentwicklungsplan 2035, Version 2031, Szenario C

class EgonScenarioCapacities(***kwargs*)
Bases: `sqlalchemy.ext.declarative.api.Base`

capacity

carrier

component

index

nuts

scenario_name

class NEP2021ConvPowerPlants(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

a2035_capacity

a2035_chp

b2035_capacity

b2035_chp

b2040_capacity

b2040_chp

bnetza_id

c2035_capacity

c2035_chp

capacity

carrier

carrier_nep

chp

city

commissioned

federal_state

index

name

name_unit

postcode

status

class ScenarioCapacities(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Create and fill table with installed generation capacities in Germany

This dataset creates and fills a table with the installed generation capacities in Germany in a lower spatial resolution (either per federal state or on national level). This data is coming from external sources (e.g. German grid developement plan for scenario eGon2035). The table is in downstream datasets used to define target values for the installed capacities.

Dependencies

- *Setup*
- *PypsaEurSec*
- *Vg250*
- *DataBundle*
- *ZensusPopulation*

Resulting tables

- *supply.egon_scenario_capacities* is created and filled

- *supply.egon_nep_2021_conventional_powerplants* is created and filled

name: str = 'ScenarioCapacities'

version: str = '0.0.13'

aggr_nep_capacities(*carriers*)
Aggregates capacities from NEP power plants list by carrier and federal state

Returns *pandas.Dataframe* – Dataframe with capacities per federal state and carrier

create_table()
Create input tables for scenario setup

Returns *None.*

district_heating_input()
Imports data for district heating networks in Germany

Returns *None.*

eGon100_capacities()
Inserts installed capacities for the eGon100 scenario

Returns *None.*

insert_capacities_per_federal_state_nep()
Inserts installed capacities per federal state accordning to NEP 2035 (version 2021), scenario 2035 C

Returns *None.*

insert_data_nep()
Overall function for importing scenario input data for eGon2035 scenario

Returns *None.*

insert_nep_list_powerplants(*export=True*)
Insert list of conventional powerplants attached to the approval of the scenario report by BNetzA

Parameters **export** (*bool*) – Choose if nep list should be exported to the data base. The default is True. If export=False a data frame will be returned

Returns **kw_liste_nep** (*pandas.DataFrame*) – List of conventional power plants from nep if export=False

map_carrier()
Map carriers from NEP and Marktstammdatenregister to carriers from eGon

Returns *pandas.Series* – List of mapped carriers

nuts_mapping()

population_share()
Calulate share of population in testmode

Returns *float* – Share of population in testmode

10.5.24 society_prognosis

The central module containing all code dealing with processing and forecast Zensus data.

class EgonHouseholdPrognosis(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

households

year

zensus_population_id

class EgonPopulationPrognosis(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

population

year

zensus_population_id

class SocietyPrognosis(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

create_tables()
Create table to map zensus grid and administrative districts (nuts3)

household_prognosis_per_year(*prognosis_nuts3*, *zensus*, *year*)
Calculate household prognosis for a specitic year

zensus_household()
Bring household prognosis from DemandRegio to Zensus grid

zensus_population()
Bring population prognosis from DemandRegio to Zensus grid

10.5.25 substation_voronoi

The central module containing code to create substation voronois

class EgonEhvSubstationVoronoi(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

geom

id

class EgonHvmvSubstationVoronoi(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

geom

id

class SubstationVoronoi(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

create_tables()
Create tables for voronoi polygons :returns: *None.*

substation_voronoi()
Creates voronoi polygons for hvmv and ehv substations

Returns *None.*

10.5.26 tyndp

The central module containing all code dealing with downloading tyndp data

class Tyndp(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Downloads data for foreign countries from Ten-Year-Network-Developement Plan

This dataset downloads installed generation capacities and load time series for foreign countries from the website of the Ten-Year-Network-Developement Plan 2020 from ENTSO-E. That data is stored into files and later on written into the database (see *ElectricalNeighbours*).

Dependencies

- Setup

Resulting tables

name: str = 'Tyndp'

version: str = '0.0.1'

download()
Download input data from TYNDP 2020 :returns: *None.*

10.5.27 vg250_mv_grid_districts

The module containing all code to map MV grid districts to federal states.

class MapMvgriddistrictsVg250(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table boundaries.egon_map_mvgriddistrict_vg250.

bus_id

vg250_lan

class Vg250MvGridDistricts(*dependencies*)
Bases: egon.data.datasets.Dataset

Maps MV grid districts to federal states and writes it to database.

Dependencies

- *Vg250*
- *MvGridDistricts*

Resulting tables

- *boundaries.egon_map_mvgriddistrict_vg250* is created and filled

name: str = 'Vg250MvGridDistricts'

version: str = '0.0.1'

create_tables()
Create table for mapping grid districts to federal states.

mapping()
Map MV grid districts to federal states and write to database.

Newly creates and fills table boundaries.egon_map_mvgriddistrict_vg250.

10.5.28 zensus_mv_grid_districts

Implements mapping between mv grid districts and zensus cells

class MapZensusGridDistricts(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table boundaries.egon_map_zensus_grid_districts.

bus_id

zensus_population_id

class ZensusMvGridDistricts(*dependencies*)
Bases: egon.data.datasets.Dataset

Maps zensus cells to MV grid districts and writes it to database.

Dependencies

- *ZensusPopulation*
- *MvGridDistricts*

Resulting tables

- *boundaries.egon_map_zensus_grid_districts* is created and filled

name: str = 'ZensusMvGridDistricts'

version: str = '0.0.1'

mapping()
Map zensus cells and MV grid districts and write to database.

Newly creates and fills table boundaries.egon_map_zensus_grid_districts.

10.5.29 zensus_vg250

class DestatisZensusPopulationPerHa(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

geom

geom_point

grid_id

id

population

x_mp

y_mp

class DestatisZensusPopulationPerHaInsideGermany(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

geom

geom_point

grid_id

id

population

class MapZensusVg250(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

vg250_municipality_id

vg250_nuts3

zensus_geom

zensus_population_id

class Vg250Gem(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

ade

ags

ags_0

ars

ars_0

bem

bez

bsg

debkg_id

fk_s3

gen

geometry

gf

ibz

id

nbd

nuts

rs

rs_0

sdv_ars

sdv_rs

sn_g

sn_k

sn_l

sn_r

sn_v1

sn_v2

wsk

class Vg250GemPopulation(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

ags_0

area_ha

area_km2

bem

bez

cell_count

gen

geom

id

nuts

population_density

population_total

rs_0

class Vg250Sta(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

ade

ags

ags_0

ars

ars_0

bem

bez

bsg

debkg_id

fk_s3

gen

geometry

gf

ibz

id

nbd

nuts

rs

rs_0

sdv_ars

sdv_rs

sn_g

sn_k

sn_l

sn_r

sn_v1

sn_v2

wsk

class ZensusVg250(*dependencies*)

Bases: *egon.data.datasets.Dataset*

name: str

The name of the Dataset

version: str

The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

add_metadata_vg250_gem_pop()

Create metadata JSON for Vg250GemPopulation

Creates a metdadata JSON string and writes it to the database table comment

add_metadata_zensus_inside_ger()

Create metadata JSON for DestatisZensusPopulationPerHaInsideGermany

Creates a metdadata JSON string and writes it to the database table comment

inside_germany()
Filter zensus data by data inside Germany and population > 0

map_zensus_vg250()
Perform mapping between municipalities and zensus grid

population_in_municipalities()
Create table of municipalities with information about population

10.5.30 chp

match_nep

The module containing all code dealing with large chp from NEP list.

insert_large_chp(*sources*, *target*, *EgonChp*)

match_nep_chp(*chp_NEP*, *MaStR_konv*, *chp_NEP_matched*, *buffer_capacity=0.1*, *consider_location='plz'*, *consider_carrier=True*, *consider_capacity=True*)
Match CHP plants from MaStR to list of power plants from NEP

Parameters

- **chp_NEP** (*pandas.DataFrame*) – CHP plants from NEP which are not matched to MaStR
- **MaStR_konv** (*pandas.DataFrame*) – CHP plants from MaStR which are not matched to NEP
- **chp_NEP_matched** (*pandas.DataFrame*) – Already matched CHP
- **buffer_capacity** (*float, optional*) – Maximum difference in capacity in p.u. The default is 0.1.

Returns

- **chp_NEP_matched** (*pandas.DataFrame*) – Matched CHP
- **MaStR_konv** (*pandas.DataFrame*) – CHP plants from MaStR which are not matched to NEP
- **chp_NEP** (*pandas.DataFrame*) – CHP plants from NEP which are not matched to MaStR

select_chp_from_mastr(*sources*)
Select combustion CHP plants from MaStR

Returns **MaStR_konv** (*pd.DataFrame*) – CHP plants from MaStR

select_chp_from_nep(*sources*)
Select CHP plants with location from NEP's list of power plants

Returns *pandas.DataFrame* – CHP plants from NEP list

small_chp

The module containing all code dealing with chp < 10MW.

`assign_use_case`(*chp*, *sources*)
Identifies CHPs used in district heating areas.

A CHP plant is assigned to a district heating area if - it is closer than 1km to the borders of the district heating area - the name of the osm landuse area where the CHP is located indicates that it feeds in to a district heating area (e.g. 'Stadtwerke') - it is not closer than 100m to an industrial area

Parameters **chp** (*pandas.DataFrame*) – CHPs without district_heating flag

Returns **chp** (*pandas.DataFrame*) – CHPs with identification of district_heating CHPs

`existing_chp_smaller_10mw`(*sources*, *MaStR_konv*, *EgonChp*)
Insert existing small CHPs based on MaStR and target values

Parameters

- **MaStR_konv** (*pandas.DataFrame*) – List of conevntional CHPs in MaStR whoes locateion is not used
- **EgonChp** (*class*) – Class definition of daabase table for CHPs

Returns **additional_capacitiy** (*pandas.Series*) – Capacity of new locations for small chp per federal state

`extension_district_heating`(*federal_state*, *additional_capacity*, *flh_chp*, *EgonChp*, *areas_without_chp_only=False*)
Build new CHP < 10 MW for district areas considering existing CHP and the heat demand.

For more details on the placement alogrithm have a look at the description of extension_to_areas().

Parameters

- **federal_state** (*str*) – Name of the federal state.
- **additional_capacity** (*float*) – Additional electrical capacity of new CHP plants in district heating
- **flh_chp** (*int*) – Assumed number of full load hours of heat output.
- **EgonChp** (*class*) – ORM-class definition of CHP database-table.
- **areas_without_chp_only** (*boolean, optional*) – Set if CHPs are only assigned to district heating areas which don't have an existing CHP. The default is True.

Returns *None.*

`extension_industrial`(*federal_state*, *additional_capacity*, *flh_chp*, *EgonChp*)
Build new CHP < 10 MW for industry considering existing CHP, osm landuse areas and electricity demands.

For more details on the placement alogrithm have a look at the description of extension_to_areas().

Parameters

- **federal_state** (*str*) – Name of the federal state.
- **additional_capacity** (*float*) – Additional electrical capacity of new CHP plants in indsutry.
- **flh_chp** (*int*) – Assumed number of full load hours of electricity output.
- **EgonChp** (*class*) – ORM-class definition of CHP database-table.

Returns *None.*

extension_per_federal_state(*federal_state*, *EgonChp*)

Adds new CHP plants to meet target value per federal state.

The additional capacity for CHPs < 10 MW is distributed discretly. Therefore, existing CHPs and their parameters from Marktstammdatenregister are randomly selected and allocated in a district heating grid. In order to generate a reasonable distribution, new CHPs can only be assigned to a district heating grid which needs additional supply technologies. This is estimated by the substraction of demand, and the assumed dispatch oof a CHP considering the capacitiy and full load hours of each CHPs.

Parameters

- **additional_capacity** (*float*) – Capacity to distribute.
- **federal_state** (*str*) – Name of the federal state
- **EgonChp** (*class*) – ORM-class definition of CHP table

Returns *None.*

extension_to_areas(*areas*, *additional_capacity*, *existing_chp*, *flh*, *EgonChp*, *district_heating=True*, *scenario='eGon2035'*)

Builds new CHPs on potential industry or district heating areas.

This method can be used to distrectly extend and spatial allocate CHP for industry or district heating areas. The following steps are running in a loop until the additional capacity is reached:

1. Randomly select an existing CHP < 10MW and its parameters.

2. Select possible areas where the CHP can be located. It is assumed that CHPs are only build if the demand of the industry or district heating grid exceeds the annual energy output of the CHP. The energy output is calculated using the installed capacity and estimated full load hours. The thermal output is used for district heating areas. Since there are no explicit heat demands for industry, the electricity output and demands are used.

3. Randomly select one of the possible areas. The areas are weighted by the annal demand, assuming that the possibility of building a CHP plant is higher when for large consumers.

4. Insert allocated CHP plant into the database

5. Substract capacity of new build CHP from the additional capacity. The energy demands of the areas are reduced by the estimated energy output of the CHP plant.

Parameters

- **areas** (*geopandas.GeoDataFrame*) – Possible areas for a new CHP plant, including their energy demand
- **additional_capacity** (*float*) – Overall eletcrical capacity of CHPs that should be build in MW.
- **existing_chp** (*pandas.DataFrame*) – List of existing CHP plants including electrical and thermal capacity
- **flh** (*int*) – Assumed electrical or thermal full load hours.
- **EgonChp** (*class*) – ORM-class definition of CHP database-table.
- **district_heating** (*boolean, optional*) – State if the areas are district heating areas. The default is True.

Returns *None.*

insert_mastr_chp(*mastr_chp*, *EgonChp*)

Insert MaStR data from exising CHPs into database table

Parameters

- **mastr_chp** (*pandas.DataFrame*) – List of existing CHPs in MaStR.
- **EgonChp** (*class*) – Class definition of daabase table for CHPs

Returns *None.*

The central module containing all code dealing with combined heat and power (CHP) plants.

class Chp(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Extract combined heat and power plants for each scenario

This dataset creates combined heat and power (CHP) plants for each scenario and defines their use case. The method bases on existing CHP plants from Marktstammdatenregister. For the eGon2035 scenario, a list of CHP plans from the grid operator is used for new largescale CHP plants. CHP < 10MW are randomly distributed. Depending on the distance to a district heating grid, it is decided if the CHP is used to supply a district heating grid or used by an industrial site.

Dependencies

- *GasAreaseGon100RE*
- *GasAreaseGon2035*
- *DistrictHeatingAreas*
- *IndustrialDemandCurves*
- *OsmLanduse*
- *download_mastr_data*
- *define_mv_grid_districts*
- *ScenarioCapacities*

Resulting tables

- *supply.egon_chp_plants* is created and filled
- *supply.egon_mastr_conventional_without_chp* is created and filled

name: str = 'Chp'

version: str = '0.0.6'

class EgonChp(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

carrier

ch4_bus_id

district_heating

district_heating_area_id

el_capacity

electrical_bus_id

geom

id

scenario

source_id

sources

th_capacity

voltage_level

class EgonMaStRConventinalWithoutChp(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

EinheitMastrNummer

carrier

city

el_capacity

federal_state

geometry

id

plz

assign_heat_bus(scenario='eGon2035')
Selects heat_bus for chps used in district heating.

Parameters scenario (*str, optional*) – Name of the corresponding scenario. The default is 'eGon2035'.

Returns *None.*

create_tables()
Create tables for chp data :returns: *None.*

extension_BB()

extension_BE()

extension_BW()

extension_BY()

extension_HB()

extension_HE()

extension_HH()

extension_MV()

extension_NS()

extension_NW()

extension_RP()

extension_SH()

extension_SL()

extension_SN()

extension_ST()

extension_TH()

insert_biomass_chp(*scenario*)
Insert biomass chp plants of future scenario

Parameters **scenario** (*str*) – Name of scenario.

Returns *None.*

insert_chp_egon100re()
Insert CHP plants for eGon100RE considering results from pypsa-eur-sec

Returns *None.*

insert_chp_egon2035()
Insert CHP plants for eGon2035 considering NEP and MaStR data

Returns *None.*

nearest(*row*, *df*, *centroid=False*, *row_geom_col='geometry'*, *df_geom_col='geometry'*, *src_column=None*)
Finds the nearest point and returns the specified column values

Parameters

- **row** (*pandas.Series*) – Data to which the nearest data of df is assigned.
- **df** (*pandas.DataFrame*) – Data which includes all options for the nearest neighbor alogrithm.
- **centroid** (*boolean*) – Use centroid geoemtry. The default is False.
- **row_geom_col** (*str, optional*) – Name of row's geometry column. The default is 'geometry'.
- **df_geom_col** (*str, optional*) – Name of df's geometry column. The default is 'geometry'.
- **src_column** (*str, optional*) – Name of returned df column. The default is None.

Returns **value** (*pandas.Series*) – Values of specified column of df

10.5.31 data_bundle

The central module containing all code dealing with small scale inpu-data

class DataBundle(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

download()
Download small scale imput data from Zenodo

10.5.32 demandregio

install_disaggregator

This module downloads and installs demandregio's disaggregator from GitHub

clone_and_install()
Clone and install repository of demandregio's disaggregator

Returns *None.*

The central module containing all code dealing with importing and adjusting data from demandRegio

class DemandRegio(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

class EgonDemandRegioCtsInd(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

demand

nuts3

scenario

wz

year

class EgonDemandRegioHH(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

demand

hh_size

nuts3

scenario

year

class EgonDemandRegioHouseholds(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

hh_size

households

nuts3

year

class EgonDemandRegioPopulation(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

nuts3

population

year

class EgonDemandRegioTimeseriesCtsInd(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

load_curve

slp

wz

year

class EgonDemandRegioWz(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

definition

sector

wz

adjust_cts_ind_nep(*ec_cts_ind*, *sector*)
Add electrical demand of new largescale CTS und industrial consumers according to NEP 2021, scneario C 2035. Values per federal state are linear distributed over all CTS branches and nuts3 regions.

Parameters **ec_cts_ind** (*pandas.DataFrame*) – CTS or industry demand without new largescale consumers.

Returns **ec_cts_ind** (*pandas.DataFrame*) – CTS or industry demand including new largescale consumers.

adjust_ind_pes(*ec_cts_ind*)
Adjust electricity demand of industrial consumers due to electrification of process heat based on assumptions of pypsa-eur-sec.

Parameters **ec_cts_ind** (*pandas.DataFrame*) – Industrial demand without additional electrification

Returns **ec_cts_ind** (*pandas.DataFrame*) – Industrial demand with additional electrification

create_tables()
Create tables for demandregio data :returns: *None.*

data_in_boundaries(*df*)
Select rows with nuts3 code within boundaries, used for testmode

Parameters **df** (*pandas.DataFrame*) – Data for all nuts3 regions

Returns *pandas.DataFrame* – Data for nuts3 regions within boundaries

disagg_households_power(*scenario*, *year*, *weight_by_income=False*, *original=False*, ***kwargs*)
Perform spatial disaggregation of electric power in [GWh/a] by key and possibly weight by income. Similar to disaggregator.spatial.disagg_households_power

Parameters

- **by** (*str*) – must be one of ['households', 'population']
- **weight_by_income** (*bool, optional*) – Flag if to weight the results by the regional income (default False)
- **orignal** (*bool, optional*) – Throughput to function households_per_size, A flag if the results should be left untouched and returned in original form for the year 2011 (True) or if they should be scaled to the given *year* by the population in that year (False).

Returns *pd.DataFrame or pd.Series*

`insert_cts_ind`(*scenario*, *year*, *engine*, *target_values*)
Calculates electrical demands of CTS and industry using demandregio's disaggregator, adjusts them according to resulting values of NEP 2021 or JRC IDEES and insert results into the database.

Parameters

- **scenario** (*str*) – Name of the corresponing scenario.
- **year** (*int*) – The number of households per region is taken from this year.
- **target_values** (*dict*) – List of target values for each scenario and sector.

Returns *None.*

`insert_cts_ind_demands`()
Insert electricity demands per nuts3-region in Germany according to demandregio using its disaggregator-tool in MWh

Returns *None.*

`insert_cts_ind_wz_definitions`()
Insert demandregio's definitions of CTS and industrial branches

Returns *None.*

`insert_hh_demand`(*scenario*, *year*, *engine*)
Calculates electrical demands of private households using demandregio's disaggregator and insert results into the database.

Parameters

- **scenario** (*str*) – Name of the corresponing scenario.
- **year** (*int*) – The number of households per region is taken from this year.

Returns *None.*

`insert_household_demand`()
Insert electrical demands for households according to demandregio using its disaggregator-tool in MWh

Returns *None.*

`insert_society_data`()
Insert population and number of households per nuts3-region in Germany according to demandregio using its disaggregator-tool

Returns *None.*

`insert_timeseries_per_wz`(*sector*, *year*)
Insert normalized electrical load time series for the selected sector

Parameters

- **sector** (*str*) – Name of the sector. ['CTS', 'industry']
- **year** (*int*) – Selected weather year

Returns *None.*

`match_nuts3_bl`()
Function that maps the federal state to each nuts3 region

Returns **df** (*pandas.DataFrame*) – List of nuts3 regions and the federal state of Germany.

timeseries_per_wz()
Calcultae and insert normalized timeseries per wz for cts and industry

Returns *None.*

10.5.33 district_heating_areas

plot

Module containing all code creating with plots of district heating areas

plot_heat_density_sorted(*heat_denisty_per_scenario*, *scenario_name=None*)
Create diagrams for visualisation, sorted by HDD sorted census dh first, sorted new areas, left overs, DH share create one dataframe with all data: first the cells with existing, then the cells with new district heating systems and in the end the ones without

Parameters

- **scenario_name** (*TYPE*) – DESCRIPTION.
- **collection** (*TYPE*) – DESCRIPTION.

Returns *None.*

Central module containing all code creating with district heating areas.

This module obtains the information from the census tables and the heat demand densities, demarcates so the current and future district heating areas. In the end it saves them in the database.

class DistrictHeatingAreas(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Create district heating grids for all scenarios

This dataset creates district heating grids for each scenario based on a defined district heating share, annual heat demands calcultaed within *HeatDemandImport* and information on existing heating grids from census *ZensusMiscellaneous*

First the tables are created using *create_tables()*. Afterwards, the distict heating grids for each scenario are created and inserted into the database by applying the function *district_heating_areas()*

Dependencies

- *HeatDemandImport*
- *ZensusMiscellaneous*
- *ScenarioParameters*

Resulting tables

- *demand.egon_map_zensus_district_heating_areas* is created and filled
- *demand.egon_district_heating_areas* is created and filled

name: str = 'district-heating-areas'

version: str = '0.0.1'

class EgonDistrictHeatingAreas(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

area_id

geom_polygon

id

residential_and_service_demand

scenario

class MapZensusDistrictHeatingAreas(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

area_id

id

scenario

zensus_population_id

add_metadata()
Writes metadata JSON string into table comment.

area_grouping(*raw_polygons*, *distance=200*, *minimum_total_demand=None*, *maximum_total_demand=None*)
Group polygons which are close to each other.

This function creates buffers around the given cell polygons (called "raw_polygons") and unions the intersecting buffer polygons. Afterwards, it unions the cell polygons which are within one unified buffer polygon. If requested, the cells being in areas fulfilling the minimum heat demand criterium are selected.

Parameters

- **raw_polygons** (*geopandas.geodataframe.GeoDataFrame*) – polygons to be grouped.
- **distance** (*integer*) – distance for buffering
- **minimum_total_demand** (*integer*) – optional minimum total heat demand to achieve a minimum size of areas
- **maximal_total_demand** (*integer*) – optional maximal total heat demand per area, if demand is higher the area is cut at nuts3 borders

Returns **join** (*geopandas.geodataframe.GeoDataFrame*) – cell polygons with area id

Notes

None

create_tables()
Create tables for district heating areas

Returns *None*

demarcation(*plotting=True*)
Load scenario specific district heating areas with metadata into database.

This function executes the functions that identifies the areas which will be supplied with district heat in the two eGo^n scenarios. The creation of heat demand density curve figures is optional. So is also the export of scenario specific Prospective Supply Districts for district heating (PSDs) as shapefiles including the creation of a figure showing the comparison of sorted heat demand densities.

The method was executed for 2015, 2035 and 2050 to find out which scenario year defines the PSDs. The year 2035 was selected and the function was adjusted accordingly. If you need the 2015 scenario heat demand data, please have a look at the heat demand script commit 270bea50332016447e869f69d51e96113073b8a0, where the 2015 scenario was deactivated. You can study the 2015 PSDs in the study_prospective_district_heating_areas function after un-commenting some lines.

Parameters **plotting** (*boolean*) – if True, figure showing the heat demand density curve will be created

Returns *None*

Notes

None

district_heating_areas(*scenario_name*, *plotting=False*)

Create scenario specific district heating areas considering on census data.

This function loads the district heating share from the scenario table and demarcate the scenario specific district heating areas. To do so it uses the census data on flats currently supplied with district heat, which are supplied selected first, if the estimated connection rate >= 30%.

All scenarios use the Prospective Supply Districts (PSDs) made for the eGon2035 scenario to identify the areas where additional district heating supply is feasible. One PSD dataset is to defined which is constant over the years to allow comparisons. Moreover, it is assumed that the eGon2035 PSD dataset is suitable, even though the heat demands will continue to decrease from 2035 to 2050, because district heating systems will be to planned and built before 2050, to exist in 2050.

It is assumed that the connection rate in cells with district heating will be a 100%. That is because later in project the number of buildings per cell will be used and connection rates not being 0 or 100% will create buildings which are not fully supplied by one technology.

The cell polygons which carry information (like heat demand etc.) are grouped into areas which are close to each other. Only cells with a minimum heat demand density (e.g. >100 GJ/(ha a)) are considered when creating PSDs. Therefore, the select_high_heat_demands() function is used. There is minimum heat demand per PSDs to achieve a certain size. While the grouping buffer for the creation of Prospective Supply Districts (PSDs) is 200m as in the sEEnergies project, the buffer for grouping census data cell with an estimated connection rate >= 30% is 500m. The 500m buffer is also used when the resulting district heating areas are grouped, because they are built upon the existing district heating systems.

To reduce the final number of district heating areas having the size of only one hectare, the minimum heat demand critrium is also applied when grouping the cells with census data on district heat.

To avoid huge district heating areas, as they appear in the Ruhr area, district heating areas with an annual demand > 4,000,000 MWh are split by nuts3 boundaries. This as set as maximum_total_demand of the area_grouping function.

Parameters

- **scenario_name** (*str*) – name of scenario to be studies
- **plotting** (*boolean*) – if True, figure showing the heat demand density curve will be created

Returns *None*

Notes

None

`load_census_data()`
Load the heating type information from the census database table.

The census apartment and the census building table contains information about the heating type. The information are loaded from the apartment table, because they might be more useful when it comes to the estimation of the connection rates. Only cells with a connection rate equal to or larger than 30% (based on the census apartment data) are included in the returned district_heat GeoDataFrame.

Parameters **None**

Returns

- **district_heat** (*geopandas.geodataframe.GeoDataFrame*) – polygons (hectare cells) with district heat information
- **heating_type** (*geopandas.geodataframe.GeoDataFrame*) – polygons (hectare cells) with the number of flats having heating type information

Notes

The census contains only information on residential buildings. Therefore, also connection rate of the residential buildings can be estimated.

`load_heat_demands(scenario_name)`
Load scenario specific heat demand data from the local database.

Parameters **scenario_name** (*str*) – name of the scenario studied

Returns **heat_demand** (*geopandas.geodataframe.GeoDataFrame*) – polygons (hectare cells) with heat demand data

`select_high_heat_demands(heat_demand)`
Take heat demand cells and select cells with higher heat demand.

Those can be used to identify prospective district heating supply areas.

Parameters **heat_demand** (*geopandas.geodataframe.GeoDataFrame*) – dataset of heat demand cells.

Returns **high_heat_demand** (*geopandas.geodataframe.GeoDataFrame*) – polygons (hectare cells) with heat demands high enough to be potentially high enough to be in a district heating area

`study_prospective_district_heating_areas()`
Get information about Prospective Supply Districts for district heating.

This optional function executes the functions so that you can study the heat demand density data of different scenarios and compare them and the resulting Prospective Supply Districts (PSDs) for district heating. This functions saves local shapefiles, because these data are not written into database. Moreover, heat density curves are drawn. This function is tailor-made and includes the scenarios eGon2035 and eGon100RE.

Parameters **None**

Returns *None*

Notes

None

10.5.34 electricity_demand

temporal

The central module containing all code dealing with processing timeseries data using demandregio

class EgonEtragoElectricityCts(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

p_set

q_set

scn_name

calc_load_curve(*share_wz*, *annual_demand=1*)
Create aggregated demand curve for service sector

Parameters

- **share_wz** (*pandas.Series or pandas.DataFrame*) – Share of annual demand per cts branch
- **annual_demand** (*float or pandas.Series, optional*) – Annual demand in MWh. The default is 1.

Returns *pandas.Series or pandas.DataFrame* – Annual load curve of combindes cts branches

calc_load_curves_cts(*scenario*)
Temporal disaggregate electrical cts demand per substation.

Parameters **scenario** (*str*) – Scenario name.

Returns *pandas.DataFrame* – Demand timeseries of cts per bus id

create_table()
Create tables for demandregio data :returns: *None.*

insert_cts_load()
Inserts electrical cts loads to etrago-tables in the database

Returns *None.*

The central module containing all code dealing with processing data from demandRegio

class CtsElectricityDemand(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

class EgonDemandRegioZensusElectricity(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

demand

scenario

sector

zensus_population_id

class HouseholdElectricityDemand(dependencies)
Bases: egon.data.datasets.Dataset

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

create_tables()
Create tables for demandregio data :returns: *None.*

distribute_cts_demands()
Distribute electrical demands for cts to zensus cells.

The demands on nuts3-level from demandregio are linear distributed to the heat demand of cts in each zensus cell.

Returns *None.*

get_annual_household_el_demand_cells()
Annual electricity demand per cell is determined

Timeseries for every cell are accumulated, the maximum value determined and with the respective nuts3 factor scaled for 2035 and 2050 scenario.

Note: In test-mode 'SH' the iteration takes place by 'cell_id' to avoid intensive RAM usage. For whole Germany 'nuts3' are taken and RAM > 32GB is necessary.

10.5.35 electricity_demand_timeseries

cts_buildings

CTS electricity and heat demand time series for scenarios in 2035 and 2050 assigned to OSM-buildings are generated.

Disaggregation of CTS heat & electricity demand time series from MV substation to census cells via annual demand and then to OSM buildings via amenity tags or randomly if no sufficient OSM-data is available in the respective census cell. If no OSM-buildings or synthetic residential buildings are available new synthetic 5x5m buildings are generated.

class BuildingHeatPeakLoads(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_building_heat_peak_loads.

building_id

peak_load_in_w

scenario

sector

class CtsBuildings(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table openstreetmap.egon_cts_buildings.

Table of all selected CTS buildings with id, census cell id, geometry and amenity count in building. This table is created within *cts_buildings()*.

geom_building

id

n_amenities_inside

serial

source

zensus_population_id

class CtsDemandBuildings(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Generates CTS electricity and heat demand time series for scenarios in 2035 and 2050 assigned to OSM-buildings.

Disaggregation of CTS heat & electricity demand time series from MV Substation to census cells via annual demand and then to OSM buildings via amenity tags or randomly if no sufficient OSM-data is available in the respective census cell. If no OSM-buildings or synthetic residential buildings are available new synthetic 5x5m buildings are generated.

Dependencies

- *OsmBuildingsStreets*
- *CtsElectricityDemand*
- *hh_buildings*
- *HeatTimeSeries* (more specifically the *export_etrago_cts_heat_profiles* task)

Resulting tables

- *openstreetmap.osm_buildings_synthetic* is extended
- :py:class:`openstreetmap.egon_cts_buildings <egon.data.datasets.electricity_demand_timeseries.cts_buildings.CtsBuild is created
- *demand.egon_cts_electricity_demand_building_share* is created
- *demand.egon_cts_heat_demand_building_share* is created
- *demand.egon_building_electricity_peak_loads* is extended
- *boundaries.egon_map_zensus_mvgd_buildings* is extended.

The following datasets from the database are mainly used for creation:

- ***openstreetmap.osm_buildings_filtered*:** Table of OSM-buildings filtered by tags to selecting residential and cts buildings only.
- ***openstreetmap.osm_amenities_shops_filtered*:** Table of OSM-amenities filtered by tags to select cts only.

- ***openstreetmap.osm_amenities_not_in_buildings_filtered*:** Table of amenities which do not intersect with any building from *openstreetmap.osm_buildings_filtered*
- ***openstreetmap.osm_buildings_synthetic*:** Table of synthetic residential buildings
- ***boundaries.egon_map_zensus_buildings_filtered_all*:** Mapping table of census cells and buildings filtered even if population in census cell = 0.
- ***demand.egon_demandregio_zensus_electricity*:** Table of annual electricity load demand for residential and cts at census cell level. Residential load demand is derived from aggregated residential building profiles. DemandRegio CTS load demand at NUTS3 is distributed to census cells linearly to heat demand from peta5.
- ***demand.egon_peta_heat*:** Table of annual heat load demand for residential and cts at census cell level from peta5.
- ***demand.egon_etrago_electricity_cts*:** Scaled cts electricity time series for every MV substation. Derived from DemandRegio SLP for selected economic sectors at nuts3. Scaled with annual demand from *demand.egon_demandregio_zensus_electricity*
- ***demand.egon_etrago_heat_cts*:** Scaled cts heat time series for every MV substation. Derived from DemandRegio SLP Gas for selected economic sectors at nuts3. Scaled with annual demand from *demand.egon_peta_heat*.

What is the goal?

To disaggregate cts heat and electricity time series from MV substation level to geo-referenced buildings, the annual demand from DemandRegio and Peta5 is used to identify census cells with load demand. We use Openstreetmap data and filter tags to identify buildings and count the amenities within. The number of amenities and the annual demand serve to assign a demand share of the MV substation profile to the building.

What is the challenge?

The OSM, DemandRegio and Peta5 dataset differ from each other. The OSM dataset is a community based dataset which is extended throughout and does not claim to be complete. Therefore, not all census cells which have a demand assigned by DemandRegio or Peta5 methodology also have buildings with respective tags or sometimes even any building at all. Furthermore, the substation load areas are determined dynamically in a previous dataset. Merging these datasets different scopes (census cell shapes, building shapes) and their inconsistencies need to be addressed. For example: not yet tagged buildings or amenities in OSM, or building shapes exceeding census cells.

How are these datasets combined?

The methodology for heat and electricity is the same and only differs in the annual demand and MV/HV Substation profile. In a previous dataset (openstreetmap), we filter all OSM buildings and amenities for tags, we relate to the cts sector. Amenities are mapped to intersecting buildings and then intersected with the annual demand which exists at census cell level. We obtain census cells with demand and amenities and without amenities. If there is no data on amenities, n synthetic ones are assigned to existing buildings. We use the median value of amenities/census cell for n and all filtered buildings + synthetic residential buildings. If no building data is available a synthetic buildings is randomly generated. This also happens for amenities which couldn't be assigned to any osm building. All census cells with an annual demand are covered this way, and we obtain four different categories of buildings with amenities:

- Buildings with amenities
- Synthetic buildings with amenities
- Buildings with synthetic amenities
- Synthetics buildings with synthetic amenities

The amenities are summed per census cell (of amenity) and building to derive the building amenity share per census cell. Multiplied with the annual demand, we receive the profile demand share for each cell. Some buildings exceed the census cell shape and have amenities in different cells although mapped to one building only. To have unique buildings the demand share is summed once more per building id. This factor can now be used to obtain the profile for each building.

A schematic flow chart exist in the correspondent issue #671: https://github.com/openego/eGon-data/issues/671#issuecomment-1260740258

What are central assumptions during the data processing?

- We assume OSM data to be the most reliable and complete open source dataset.
- We assume building and amenity tags to be truthful and accurate.
- Mapping census to OSM data is not trivial. Discrepancies are substituted.
- Missing OSM buildings are generated for each amenity.
- Missing amenities are generated by median value of amenities/census cell.

Drawbacks and limitations of the data

- Shape of profiles for each building is similar within a MVGD and only scaled with a different factor.
- MVGDs are generated dynamically. In case of buildings with amenities exceeding MVGD borders, amenities which are assigned to a different MVGD than the assigned building centroid, the amenities are dropped for sake of simplicity. One building should not have a connection to two MVGDs.
- The completeness of the OSM data depends on community contribution and is crucial to the quality of our results.
- Randomly selected buildings and generated amenities may inadequately reflect reality, but are chosen for sake of simplicity as a measure to fill data gaps.
- Since this dataset is a cascade after generation of synthetic residential buildings also check drawbacks and limitations in hh_buildings.py.
- Synthetic buildings may be placed within osm buildings which exceed multiple census cells. This is currently accepted but may be solved in #953.
- Scattered high peak loads occur and might lead to single MV grid connections in ding0. In some cases this might not be viable. Postprocessing is needed and may be solved in #954.

name: str = 'CtsDemandBuildings'

version: str = '0.0.3'

class EgonCtsElectricityDemandBuildingShare(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

Class definition of table demand.egon_cts_electricity_demand_building_share.

Table including the MV substation electricity profile share of all selected CTS buildings for scenario eGon2035 and eGon100RE. This table is created within *cts_electricity()*.

building_id

bus_id

profile_share

scenario

class EgonCtsHeatDemandBuildingShare(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_cts_heat_demand_building_share.

Table including the MV substation heat profile share of all selected CTS buildings for scenario eGon2035 and eGon100RE. This table is created within cts_heat().

building_id

bus_id

profile_share

scenario

amenities_without_buildings()
Amenities which have no buildings assigned and are in a cell with cts demand are determined.

Returns *pd.DataFrame* – Table of amenities without buildings

assign_voltage_level_to_buildings()
Add voltage level to all buildings by summed peak demand.

All entries with same building id get the voltage level corresponding to their summed residential and cts peak demand.

buildings_with_amenities()
Amenities which are assigned to buildings are determined and grouped per building and zensus cell. Buildings covering multiple cells therefore exists multiple times but in different zensus cells. This is necessary to cover as many cells with a cts demand as possible. If buildings exist in multiple mvgds (bus_id) , only the amenities within the same as the building centroid are kept. If as a result, a census cell is uncovered by any buildings, a synthetic amenity is placed. The buildings are aggregated afterwards during the calculation of the profile_share.

Returns

- **df_buildings_with_amenities** (*gpd.GeoDataFrame*) – Contains all buildings with amenities per zensus cell.
- **df_lost_cells** (*gpd.GeoDataFrame*) – Contains synthetic amenities in lost cells. Might be empty

buildings_without_amenities()
Buildings (filtered and synthetic) in cells with cts demand but no amenities are determined.

Returns **df_buildings_without_amenities** (*gpd.GeoDataFrame*) – Table of buildings without amenities in zensus cells with cts demand.

calc_building_demand_profile_share(*df_cts_buildings*, *scenario='eGon2035'*, *sector='electricity'*)
Share of cts electricity demand profile per bus for every selected building is calculated. Building-amenity share is multiplied with census cell share to get the substation bus profile share for each building. The share is grouped and aggregated per building as some buildings exceed the shape of census cells and have amenities assigned from multiple cells. Building therefore get the amenity share of all census cells.

Parameters

- **df_cts_buildings** (*gpd.GeoDataFrame*) – Table of all buildings with cts demand assigned
- **scenario** (*str*) – Scenario for which the share is calculated.
- **sector** (*str*) – Sector for which the share is calculated.

Returns **df_building_share** (*pd.DataFrame*) – Table of bus profile share per building

calc_census_cell_share(*scenario*, *sector*)

The profile share for each census cell is calculated by it's share of annual demand per substation bus. The annual demand per cell is defined by DemandRegio/Peta5. The share is for both scenarios identical as the annual demand is linearly scaled.

Parameters

- **scenario** (*str*) – Scenario for which the share is calculated: "eGon2035" or "eGon100RE"
- **sector** (*str*) – Scenario for which the share is calculated: "electricity" or "heat"

Returns **df_census_share** (*pd.DataFrame*)

calc_cts_building_profiles(*bus_ids*, *scenario*, *sector*)

Calculate the cts demand profile for each building. The profile is calculated by the demand share of the building per substation bus.

Parameters

- **bus_ids** (*list of int*) – Ids of the substation for which selected building profiles are calculated.
- **scenario** (*str*) – Scenario for which the share is calculated: "eGon2035" or "eGon100RE"
- **sector** (*str*) – Sector for which the share is calculated: "electricity" or "heat"

Returns **df_building_profiles** (*pd.DataFrame*) – Table of demand profile per building. Column names are building IDs and index is hour of the year as int (0-8759).

cells_with_cts_demand_only(*df_buildings_without_amenities*)

Cells with cts demand but no amenities or buildilngs are determined.

Returns **df_cells_only_cts_demand** (*gpd.GeoDataFrame*) – Table of cells with cts demand but no amenities or buildings

create_synthetic_buildings(*df*, *points=None*, *crs='EPSG:3035'*)

Synthetic buildings are generated around points.

Parameters

- **df** (*pd.DataFrame*) – Table of census cells
- **points** (*gpd.GeoSeries or str*) – List of points to place buildings around or column name of df
- **crs** (*str*) – CRS of result table

Returns **df** (*gpd.GeoDataFrame*) – Synthetic buildings

cts_buildings()

Assigns CTS demand to buildings and calculates the respective demand profiles. The demand profile per substation are disaggregated per annual demand share of each census cell and by the number of amenities per building within the cell. If no building data is available, synthetic buildings are generated around the amenities. If no amenities but cts demand is available, buildings are randomly selected. If no building nor amenity is available, random synthetic buildings are generated. The demand share is stored in the database.

Cells with CTS demand, amenities and buildings do not change within the scenarios, only the demand itself. Therefore scenario eGon2035 can be used universally to determine the cts buildings but not for the demand share.

cts_electricity()

Calculate cts electricity demand share of hvmv substation profile for buildings.

cts_heat()

Calculate cts electricity demand share of hvmv substation profile for buildings.

delete_synthetic_cts_buildings()
All synthetic cts buildings are deleted from the DB. This is necessary if the task is run multiple times as the existing synthetic buildings influence the results.

get_cts_electricity_peak_load()
Get electricity peak load of all CTS buildings for both scenarios and store in DB.

get_cts_heat_peak_load()
Get heat peak load of all CTS buildings for both scenarios and store in DB.

get_peta_demand(*mvgd*, *scenario*)
Retrieve annual peta heat demand for CTS for either eGon2035 or eGon100RE scenario.

Parameters

- **mvgd** (*int*) – ID of substation for which to get CTS demand.
- **scenario** (*str*) – Possible options are eGon2035 or eGon100RE

Returns **df_peta_demand** (*pd.DataFrame*) – Annual residential heat demand per building and scenario. Columns of the dataframe are zensus_population_id and demand.

place_buildings_with_amenities(*df*, *amenities=None*, *max_amenities=None*)
Building centroids are placed randomly within census cells. The Number of buildings is derived from n_amenity_inside, the selected method and number of amenities per building.

Returns **df** (*gpd.GeoDataFrame*) – Table of buildings centroids

remove_double_bus_id(*df_cts_buildings*)
This is an backup adhoc fix if there should still be a building which is assigned to 2 substations. In this case one of the buildings is just dropped. As this currently accounts for only one building with one amenity the deviation is neglectable.

select_cts_buildings(*df_buildings_wo_amenities*, *max_n*)
N Buildings (filtered and synthetic) in each cell with cts demand are selected. Only the first n buildings are taken for each cell. The buildings are sorted by surface area.

Returns **df_buildings_with_cts_demand** (*gpd.GeoDataFrame*) – Table of buildings

hh_buildings

Household electricity demand time series for scenarios in 2035 and 2050 assigned to OSM-buildings.

class BuildingElectricityPeakLoads(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_building_electricity_peak_loads.

Mapping of electricity demand time series and buildings including cell_id, building area and peak load. This table is created within hh_buildings.get_building_peak_loads().

building_id

peak_load_in_w

scenario

sector

voltage_level

class HouseholdElectricityProfilesOfBuildings(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_household_electricity_profile_of_buildings.

Mapping of demand timeseries and buildings and cell_id. This table is created within hh_buildings.map_houseprofiles_to_buildings().

building_id

cell_id

id

profile_id

class OsmBuildingsSynthetic(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.osm_buildings_synthetic.

Lists generated synthetic building with id, zensus_population_id and building type. This table is created within hh_buildings.map_houseprofiles_to_buildings().

area

building

cell_id

geom_building

geom_point

id

n_amenities_inside

generate_mapping_table(*egon_map_zensus_buildings_residential_synth*, *egon_hh_profile_in_zensus_cell*)
Generate a mapping table for hh profiles to buildings.

All hh demand profiles are randomly assigned to buildings within the same cencus cell.

- **profiles > buildings: buildings can have multiple profiles but every** building gets at least one profile
- profiles < buildings: not every building gets a profile

Parameters

- **egon_map_zensus_buildings_residential_synth** (*pd.DataFrame*) – Table with OSM and synthetic buildings ids per census cell
- **egon_hh_profile_in_zensus_cell** (*pd.DataFrame*) – Table mapping hh demand profiles to census cells

Returns *pd.DataFrame* – Table with mapping of profile ids to buildings with OSM ids

generate_synthetic_buildings(*missing_buildings*, *edge_length*)
Generate synthetic square buildings in census cells for every entry in missing_buildings.

Generate random placed synthetic buildings incl geom data within the bounds of the cencus cell. Buildings have each a square area with edge_length^2.

Parameters

- **missing_buildings** (*pd.Series or pd.DataFrame*) – Table with cell_ids and building number
- **edge_length** (*int*) – Edge length of square synthetic building in meter

Returns *pd.DataFrame* – Table with generated synthetic buildings, area, cell_id and geom data

`get_building_peak_loads`()

Peak loads of buildings are determined.

Timeseries for every building are accumulated, the maximum value determined and with the respective nuts3 factor scaled for 2035 and 2050 scenario.

Note: In test-mode 'SH' the iteration takes place by 'cell_id' to avoid intensive RAM usage. For whole Germany 'nuts3' are taken and RAM > 32GB is necessary.

`map_houseprofiles_to_buildings`()

Cencus hh demand profiles are assigned to buildings via osm ids. If no OSM ids available, synthetic buildings are generated. A list of the generated buildings and supplementary data as well as the mapping table is stored in the db.

synthetic_buildings: schema: openstreetmap tablename: osm_buildings_synthetic

mapping_profiles_to_buildings: schema: demand tablename: egon_household_electricity_profile_of_buildings

Notes

`match_osm_and_zensus_data`(*egon_hh_profile_in_zensus_cell*, *egon_map_zensus_buildings_residential*)

Compares OSM buildings and census hh demand profiles.

OSM building data and hh demand profiles based on census data is compared. Census cells with only profiles but no osm-ids are identified to generate synthetic buildings. Census building count is used, if available, to define number of missing buildings. Otherwise, the overall mean profile/building rate is used to derive the number of buildings from the number of already generated demand profiles.

Parameters

- **egon_hh_profile_in_zensus_cell** (*pd.DataFrame*) – Table mapping hh demand profiles to census cells
- **egon_map_zensus_buildings_residential** (*pd.DataFrame*) – Table with buildings osm-id and cell_id

Returns *pd.DataFrame* – Table with cell_ids and number of missing buildings

`reduce_synthetic_buildings`(*mapping_profiles_to_buildings*, *synthetic_buildings*)

Reduced list of synthetic buildings to amount actually used.

Not all are used, due to randomised assignment with replacing Id's are adapted to continuous number sequence following openstreetmap.osm_buildings

`class setup`(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Household electricity demand time series for scenarios in 2035 and 2050 assigned to OSM-buildings.

Assignment of household electricity demand timeseries to OSM buildings and generation of randomly placed synthetic 5x5m buildings if no sufficient OSM-data available in the respective census cell.

Dependencies

- *houseprofiles_in_census_cells*

Resulting tables

- `OsmBuildingsSynthetic` is created and filled
- `HouseholdElectricityProfilesOfBuildings` is created and filled
- `BuildingElectricityPeakLoads` is created and filled

The following datasets from the database are used for creation:

- ***demand.household_electricity_profiles_in_census_cells*:** Lists references and scaling parameters to time series data for each household in a cell by identifiers. This table is fundamental for creating subsequent data like demand profiles on MV grid level or for determining the peak load at load. Only the profile reference and the cell identifiers are used.
- ***society.egon_destatis_zensus_apartment_building_population_per_ha*:** Lists number of apartments, buildings and population for each census cell.
- ***boundaries.egon_map_zensus_buildings_residential*:** List of OSM tagged buildings which are considered to be residential.

What is the goal?

To assign every household demand timeseries, which already exist at cell level, to a specific OSM building.

What is the challenge?

The census and the OSM dataset differ from each other. The census uses statistical methods and therefore lacks accuracy at high spatial resolution. The OSM datasets is community based dataset which is extended throughout and does not claim to be complete. By merging these datasets inconsistencies need to be addressed. For example: not yet tagged buildings in OSM or new building areas not considered in census 2011.

How are these datasets combined?

The assignment of household demand timeseries to buildings takes place at cell level. Within each cell a pool of profiles exists, produced by the 'HH Demand" module. These profiles are randomly assigned to a filtered list of OSM buildings within this cell. Every profile is assigned to a building and every building get a profile assigned if there is enough households by the census data. If there are more profiles than buildings, all additional profiles are randomly assigned. Therefore, multiple profiles can be assigned to one building, making it a multi-household building.

What are central assumptions during the data processing?

- Mapping zensus data to OSM data is not trivial. Discrepancies are substituted.
- Missing OSM buildings are generated by census building count.
- If no census building count data is available, the number of buildings is derived by an average rate of households/buildings applied to the number of households.

Drawbacks and limitations of the data

- Missing OSM buildings in cells without census building count are derived by an average rate of households/buildings applied to the number of households. As only whole houses can exist, the substitute is ceiled to the next higher integer. Ceiling is applied to avoid rounding to amount of 0 buildings.
- As this datasets is a cascade after profile assignement at census cells also check drawbacks and limitations in hh_profiles.py.

- Get a list with number of houses, households and household types per census cell

```
SELECT t1.cell_id, building_count, hh_count, hh_types FROM (
    SELECT
        cell_id,
        COUNT(DISTINCT(building_id)) AS building_count,
        COUNT(profile_id) AS hh_count
    FROM demand.egon_household_electricity_profile_of_buildings
    GROUP BY cell_id
) AS t1
FULL OUTER JOIN (
    SELECT
        cell_id,
        array_agg(
            array[CAST(hh_10types AS char), hh_type]
        ) AS hh_types
    FROM society.egon_destatis_zensus_household_per_ha_refined
    GROUP BY cell_id
) AS t2
ON t1.cell_id = t2.cell_id
```

name: str = 'Demand_Building_Assignment'

tasks: *egon.data.datasets.Tasks* = (<function map_houseprofiles_to_buildings>, <function get_building_peak_loads>)

version: str = '0.0.5'

hh_profiles

Household electricity demand time series for scenarios eGon2035 and eGon100RE at census cell level are set up.

Electricity demand data for households in Germany in 1-hourly resolution for an entire year. Spatially, the data is resolved to 100 x 100 m cells and provides individual and distinct time series for each household in a cell. The cells are defined by the dataset Zensus 2011.

class EgonDestatisZensusHouseholdPerHaRefined(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

Class definition of table society.egon_destatis_zensus_household_per_ha_refined.

cell_id

characteristics_code

grid_id

hh_10types

hh_5types

hh_type

id

nuts1

nuts3

class EgonEtragoElectricityHouseholds(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

Class definition of table demand.egon_etrago_electricity_households.

The table contains household electricity demand profiles aggregated at MV grid district level in MWh.

bus_id

p_set

q_set

scn_name

class HouseholdDemands(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Household electricity demand time series for scenarios eGon2035 and eGon100RE at census cell level are set up.

Electricity demand data for households in Germany in 1-hourly resolution for an entire year. Spatially, the data is resolved to 100 x 100 m cells and provides individual and distinct time series for each household in a cell. The cells are defined by the dataset Zensus 2011.

Dependencies

- *DemandRegio*
- *Vg250*
- *OsmBuildingsStreets*
- *create_buildings_residential_zensus_mapping*
- *ZensusMiscellaneous*
- *ZensusMvGridDistricts*
- *ZensusVg250*

Resulting tables

- *demand.iee_household_load_profiles* is created and filled
- *demand.egon_household_electricity_profile_in_census_cell* is created and filled
- *society.egon_destatis_zensus_household_per_ha_refined* is created and filled
- *demand.egon_etrago_electricity_households* is created and filled

The following datasets are used for creating the data:

- Electricity demand time series for household categories produced by demand profile generator (DPG) from Fraunhofer IEE (see *get_iee_hh_demand_profiles_raw()*)
- Spatial information about people living in households by Zensus 2011 at federal state level
  - Type of household (family status)
  - Age
  - Number of people
- Spatial information about number of households per ha, categorized by type of household (family status) with 5 categories (also from Zensus 2011)
- Demand-Regio annual household demand at NUTS3 level

What is the goal?

To use the electricity demand time series from the *demand profile generator* to created spatially reference household demand time series for Germany at a resolution of 100 x 100 m cells.

What is the challenge?

The electricity demand time series produced by demand profile generator offer 12 different household profile categories. To use most of them, the spatial information about the number of households per cell (5 categories) needs to be enriched by supplementary data to match the household demand profile categories specifications. Hence, 10 out of 12 different household profile categories can be distinguished by increasing the number of categories of cell-level household data.

How are these datasets combined?

- Spatial information about people living in households by zensus (2011) at federal state NUTS1 level *df_zensus* is aggregated to be compatible to IEE household profile specifications.
  - exclude kids and reduce to adults and seniors
  - group as defined in *HH_TYPES*
  - convert data from people living in households to number of households by *mapping_people_in_households*
  - calculate fraction of fine household types (10) within subgroup of rough household types (5) *df_dist_households*
- Spatial information about number of households per ha *df_census_households_nuts3* is mapped to NUTS1 and NUTS3 level. Data is refined with household subgroups via *df_dist_households* to *df_census_households_grid_refined*.
- Enriched 100 x 100 m household dataset is used to sample and aggregate household profiles. A table including individual profile id's for each cell and scaling factor to match Demand-Regio annual sum projections for 2035 and 2050 at NUTS3 level is created in the database as *demand.household_electricity_profiles_in_census_cells*.

What are central assumptions during the data processing?

- Mapping zensus data to IEE household categories is not trivial. In conversion from persons in household to number of households, number of inhabitants for multi-person households is estimated as weighted average in *OO_factor*
- The distribution to refine household types at cell level are the same for each federal state
- Refining of household types lead to float number of profiles drew at cell level and need to be rounded to nearest int by np.rint().
- 100 x 100 m cells are matched to NUTS via cells centroid location
- Cells with households in unpopulated areas are removed

Drawbacks and limitations of the data

- The distribution to refine household types at cell level are the same for each federal state
- Household profiles aggregated annual demand matches Demand Regio demand at NUTS-3 level, but it is not matching the demand regio time series profile
- Due to secrecy, some census data are highly modified under certain attributes (quantity_q = 2). This cell data is not corrected, but excluded.
- There is deviation in the Census data from table to table. The statistical methods are not stringent. Hence, there are cases in which data contradicts.
- Census data with attribute 'HHTYP_FAM' is missing for some cells with small amount of households. This data is generated using the average share of household types for cells with similar household number. For some cells the summed amount of households per type deviates from the total number with attribute

'INSGESAMT'. As the profiles are scaled with demand-regio data at nuts3-level the impact at a higher aggregation level is negligible. For sake of simplicity, the data is not corrected.

- There are cells without household data but a population. A randomly chosen household distribution is taken from a subgroup of cells with same population value and applied to all cells with missing household distribution and the specific population value.

Helper functions * To access the DB, select specific profiles at various aggregation levels

use *get_hh_profiles_from_db()*

- To access the DB, select specific profiles at various aggregation levels and scale profiles use *get_scaled_profiles_from_db()*

name: str = 'Household Demands'

version: str = '0.0.10'

class HouseholdElectricityProfilesInCensusCells(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_household_electricity_profile_in_census_cell.

Lists references and scaling parameters of time series data for each household in a cell by identifiers. This table is fundamental for creating subsequent data like demand profiles on MV grid level or for determining the peak load at load area level.

cell_id

cell_profile_ids

factor_2035

factor_2050

grid_id

nuts1

nuts3

class IeeHouseholdLoadProfiles(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.iee_household_load_profiles.

id

load_in_wh

type

adjust_to_demand_regio_nuts3_annual(*df_hh_profiles_in_census_cells*, *df_iee_profiles*, *df_demand_regio*)

Computes the profile scaling factor for alignment to demand regio data

The scaling factor can be used to re-scale each load profile such that the sum of all load profiles within one NUTS-3 area equals the annual demand of demand regio data.

Parameters

- **df_hh_profiles_in_census_cells** (*pd.DataFrame*) – Result of *assign_hh_demand_profiles_to_cells()*.
- **df_iee_profiles** (*pd.DataFrame*) – Household load profile data
  - Index: Times steps as serial integers

  - Columns: pd.MultiIndex with (*HH_TYPE*, *id*)

- **df_demand_regio** (*pd.DataFrame*) – Annual demand by demand regio for each NUTS-3 region and scenario year. Index is pd.MultiIndex with `tuple(scenario_year, nuts3_code)`.

Returns *pd.DataFrame* – Returns the same data as *assign_hh_demand_profiles_to_cells()*, but with filled columns *factor_2035* and *factor_2050*.

`assign_hh_demand_profiles_to_cells`(*df_zensus_cells*, *df_iee_profiles*)

Assign household demand profiles to each census cell.

A table including the demand profile ids for each cell is created by using *get_cell_demand_profile_ids()*. Household profiles are randomly sampled for each cell. The profiles are not replaced to the pool within a cell but after.

Parameters

- **df_zensus_cells** (*pd.DataFrame*) – Household type parameters. Each row representing one household. Hence, multiple rows per zensus cell.
- **df_iee_profiles** (*pd.DataFrame*) – Household load profile data
  - Index: Times steps as serial integers
  - Columns: pd.MultiIndex with (*HH_TYPE*, *id*)

Returns *pd.DataFrame* – Tabular data with one row represents one zensus cell. The column *cell_profile_ids* contains a list of tuples (see *get_cell_demand_profile_ids()*) providing a reference to the actual load profiles that are associated with this cell.

`clean`(*x*)

Clean zensus household data row-wise

Clean dataset by

- converting '.' and '-' to str(0)
- removing brackets

Table can be converted to int/floats afterwards

Parameters **x** (*pd.Series*) – It is meant to be used with `df.applymap()`

Returns *pd.Series* – Re-formatted data row

`create_missing_zensus_data`(*df_households_typ*, *df_missing_data*, *missing_cells*)

Generate missing data as average share of the household types for cell groups with the same amount of households.

There is missing data for specific attributes in the zensus dataset because of secrecy reasons. Some cells with only small amount of households are missing with attribute HHTYP_FAM. However the total amount of households is known with attribute INSGESAMT. The missing data is generated as average share of the household types for cell groups with the same amount of households.

Parameters

- **df_households_typ** (*pd.DataFrame*) – Zensus households data
- **df_missing_data** (*pd.DataFrame*) – number of missing cells of group of amount of households
- **missing_cells** (*dict*) – dictionary with list of grids of the missing cells grouped by amount of households in cell

Returns **df_average_split** (*pd.DataFrame*) – generated dataset of missing cells

get_cell_demand_metadata_from_db(*attribute*, *list_of_identifiers*)
Retrieve selection of household electricity demand profile mapping

Parameters

- **attribute** (*str*) – attribute to filter the table
  - nuts3
  - nuts1
  - cell_id
- **list_of_identifiers** (*list of str/int*) – nuts3/nuts1 need to be str cell_id need to be int

See also:

houseprofiles_in_census_cells()

Returns *pd.DataFrame* – Selection of mapping of household demand profiles to zensus cells

get_cell_demand_profile_ids(*df_cell*, *pool_size*)
Generates tuple of hh_type and zensus cell ids

Takes a random sample of profile ids for given cell:

- if pool size >= sample size: without replacement
- if pool size < sample size: with replacement

Parameters

- **df_cell** (*pd.DataFrame*) – Household type information for a single zensus cell
- **pool_size** (*int*) – Number of available profiles to select from

Returns *list of tuple* – List of (*hh_type*, *cell_id*)

get_census_households_grid()
Retrieves and adjusts census household data at 100x100m grid level, accounting for missing or divergent data.

Query census household data at 100x100m grid level from database. As there is a divergence in the census household data depending which attribute is used. There also exist cells without household but with population data. The missing data in these cases are substituted. First census household data with attribute 'HHTYP_FAM' is missing for some cells with small amount of households. This data is generated using the average share of household types for cells with similar household number. For some cells the summed amount of households per type deviates from the total number with attribute 'INSGESAMT'. As the profiles are scaled with demand-regio data at nuts3-level the impact at a higher aggregation level is negligible. For sake of simplicity, the data is not corrected.

Returns *pd.DataFrame* – census household data at 100x100m grid level

get_census_households_nuts1_raw()
Get zensus age x household type data from egon-data-bundle

Dataset about household size with information about the categories:

- family type
- age class
- household size

for Germany in spatial resolution of federal states NUTS-1.

Data manually selected and retrieved from: https://ergebnisse2011.zensus2022.de/datenbank/online For reproducing data selection, please do:

- Search for: "1000A-3016"
- or choose topic: "Bevölkerung kompakt"
- Choose table code: "1000A-3016" with title "Personen: Alter (11 Altersklassen) - Größe des privaten Haushalts - Typ des privaten Haushalts (nach Familien/Lebensform)"
- Change setting "GEOLK1" to "Bundesländer (16)"

Data would be available in higher resolution ("Landkreise und kreisfreie Städte (412)"), but only after registration.

The downloaded file is called 'Zensus2011_Personen.csv'.

Returns *pd.DataFrame* – Pre-processed zensus household data

`get_hh_profiles_from_db`(*profile_ids*)

Retrieve selection of household electricity demand profiles

Parameters **profile_ids** (*list of str (str, int)*) – (type)a00..(profile number) with number having exactly 4 digits

See also:

houseprofiles_in_census_cells()

Returns *pd.DataFrame* – Selection of household demand profiles

`get_houseprofiles_in_census_cells`()

Retrieve household electricity demand profile mapping from database

See also:

houseprofiles_in_census_cells()

Returns *pd.DataFrame* – Mapping of household demand profiles to zensus cells

`get_iee_hh_demand_profiles_raw`()

Gets and returns household electricity demand profiles from the egon-data-bundle.

Household electricity demand profiles generated by Fraunhofer IEE. Methodology is described in Erzeugung zeitlich hochaufgelöster Stromlastprofile für verschiedene Haushaltstypen. It is used and further described in the following theses by:

- Jonas Haack: "Auswirkungen verschiedener Haushaltslastprofile auf PV-Batterie-Systeme" (confidential)
- Simon Ruben Drauz "Synthesis of a heat and electrical load profile for single and multi-family houses used for subsequent performance tests of a multi-component energy system", http://dx.doi.org/10.13140/RG.2.2.13959.14248

Notes

The household electricity demand profiles have been generated for 2016 which is a leap year (8784 hours) starting on a Friday. The weather year is 2011 and the heat timeseries 2011 are generated for 2011 too (cf. dataset `egon.data.datasets.heat_demand_timeseries.HTS`), having 8760h and starting on a Saturday. To align the profiles, the first day of the IEE profiles are deleted, resulting in 8760h starting on Saturday.

Returns *pd.DataFrame* – Table with profiles in columns and time as index. A pd.MultiIndex is used to distinguish load profiles from different EUROSTAT household types.

`get_load_timeseries`(*df_iee_profiles*, *df_hh_profiles_in_census_cells*, *cell_ids*, *year*, *aggregate=True*, *peak_load_only=False*)

Get peak load for one load area in MWh

The peak load is calculated in aggregated manner for a group of zensus cells that belong to one load area (defined by *cell_ids*).

Parameters

- **df_iee_profiles** (*pd.DataFrame*) – Household load profile data in Wh
  - Index: Times steps as serial integers
  - Columns: pd.MultiIndex with (*HH_TYPE*, *id*)

  Used to calculate the peak load from.
- **df_hh_profiles_in_census_cells** (*pd.DataFrame*) – Return value of *adjust_to_demand_regio_nuts3_annual()*.
- **cell_ids** (*list*) – Zensus cell ids that define one group of zensus cells that belong to the same load area.
- **year** (*int*) – Scenario year. Is used to consider the scaling factor for aligning annual demand to NUTS-3 data.
- **aggregate** (*bool*) – If true, all profiles are aggregated
- **peak_load_only** (*bool*) – If true, only the peak load value is returned (the type of the return value is *float*). Defaults to False which returns the entire time series as pd.Series.

Returns *pd.Series or float* – Aggregated time series for given *cell_ids* or peak load of this time series in MWh.

`get_scaled_profiles_from_db`(*attribute*, *list_of_identifiers*, *year*, *aggregate=True*, *peak_load_only=False*)

Retrieve selection of scaled household electricity demand profiles

Parameters

- **attribute** (*str*) – attribute to filter the table
  - nuts3
  - nuts1
  - cell_id
- **list_of_identifiers** (*list of str/int*) – nuts3/nuts1 need to be str cell_id need to be int
- **year** (*int*) –
  - 2035
  - 2050

- **aggregate** (*bool*) – If True, all profiles are summed. This uses a lot of RAM if a high attribute level is chosen
- **peak_load_only** (*bool*) – If True, only peak load value is returned

Notes

Aggregate == False option can use a lot of RAM if many profiles are selected

Returns *pd.Series or float* – Aggregated time series for given *cell_ids* or peak load of this time series in MWh.

houseprofiles_in_census_cells()

Allocate household electricity demand profiles for each census cell.

Creates table *emand.egon_household_electricity_profile_in_census_cell* that maps household electricity demand profiles to census cells. Each row represents one cell and contains a list of profile IDs. This table is fundamental for creating subsequent data like demand profiles on MV grid level or for determining the peak load at load area level.

Use *get_houseprofiles_in_census_cells()* to retrieve the data from the database as pandas.

impute_missing_hh_in_populated_cells(*df_census_households_grid*)

Fills in missing household data in populated cells based on a random selection from a subgroup of cells with the same population value.

There are cells without household data but a population. A randomly chosen household distribution is taken from a subgroup of cells with same population value and applied to all cells with missing household distribution and the specific population value. In the case, in which there is no subgroup with household data of the respective population value, the fallback is the subgroup with the last last smaller population value.

Parameters **df_census_households_grid** (*pd.DataFrame*) – census household data at 100x100m grid level

Returns *pd.DataFrame* – substituted census household data at 100x100m grid level

inhabitants_to_households(*df_hh_people_distribution_abs*)

Convert number of inhabitant to number of household types

Takes the distribution of peoples living in types of households to calculate a distribution of household types by using a people-in-household mapping. Results are not rounded to int as it will be used to calculate a relative distribution anyways. The data of category 'HHGROESS_KLASS' in census households at grid level is used to determine an average wherever the amount of people is not trivial (OR, OO). Kids are not counted.

Parameters **df_hh_people_distribution_abs** (*pd.DataFrame*) – Grouped census household data on NUTS-1 level in absolute values

Returns **df_dist_households** (*pd.DataFrame*) – Distribution of households type

mv_grid_district_HH_electricity_load(*scenario_name*, *scenario_year*, *drop_table=False*)

Aggregated household demand time series at HV/MV substation level

Calculate the aggregated demand time series based on the demand profiles of each zensus cell inside each MV grid district. Profiles are read from local hdf5-file. Creates table *demand.egon_etrago_electricity_households* with Household electricity demand profiles aggregated at MV grid district level in MWh. Primarily used to create the eTraGo data model.

Parameters

- **scenario_name** (*str*) – Scenario name identifier, i.e. "eGon2035"
- **scenario_year** (*int*) – Scenario year according to *scenario_name*

- **drop_table** (*bool*) – Toggle to True for dropping table at beginning of this function. Be careful, delete any data.

Returns *pd.DataFrame* – Multiindexed dataframe with *timestep* and *bus_id* as indexers. Demand is given in kWh.

`process_nuts1_census_data`(*df_census_households_raw*)

Make data compatible with household demand profile categories

Removes and reorders categories which are not needed to fit data to household types of IEE electricity demand time series generated by demand-profile-generator (DPG).

- Kids (<15) are excluded as they are also excluded in DPG origin dataset
- Adults (15<65)
- Seniors (<65)

Parameters **df_census_households_raw** (*pd.DataFrame*) – cleaned zensus household type x age category data

Returns *pd.DataFrame* – Aggregated zensus household data on NUTS-1 level

`proportionate_allocation`(*df_group*, *dist_households_nuts1*, *hh_10types_cluster*)

Household distribution at nuts1 are applied at census cell within group

To refine the hh_5types and keep the distribution at nuts1 level, the household types are clustered and drawn with proportionate weighting. The resulting pool is splitted into subgroups with sizes according to the number of households of clusters in cells.

Parameters

- **df_group** (*pd.DataFrame*) – Census household data at grid level for specific hh_5type cluster in a federal state
- **dist_households_nuts1** (*pd.Series*) – Household distribution of of hh_10types in a federal state
- **hh_10types_cluster** (*list of str*) – Cluster of household types to be refined to

Returns *pd.DataFrame* – Refined household data with hh_10types of cluster at nuts1 level

`refine_census_data_at_cell_level`(*df_census_households_grid*, *df_census_households_nuts1*)

Processes and merges census data to specify household numbers and types per census cell according to IEE profiles.

The census data is processed to define the number and type of households per zensus cell. Two subsets of the census data are merged to fit the IEE profiles specifications. To do this, proportionate allocation is applied at nuts1 level and within household type clusters.

Header “characteristics_code”, “characteristics_text”, “mapping”

“1”, “Einpersonenhaushalte (Singlehaushalte)”, “SR; SO” “2”, “Paare ohne Kind(er)”, “PR; PO” “3”, “Paare mit Kind(ern)”, “P1; P2; P3” “4”, “Alleinerziehende Elternteile”, “SK” “5”, “Mehrpersonenhaushalte ohne Kernfamilie”, “OR; OO”

Parameters

- **df_census_households_grid** (*pd.DataFrame*) – Aggregated zensus household data on 100x100m grid level
- **df_census_households_nuts1** (*pd.DataFrame*) – Aggregated zensus household data on NUTS-1 level

Returns *pd.DataFrame* – Number of hh types per census cell

`regroup_nuts1_census_data`(*df_census_households_nuts1*)
Regroup census data and map according to demand-profile types.

For more information look at the respective publication: https://www.researchgate.net/publication/273775902_Erzeugung_zeitlich_hochaufgeloster_Stromlastprofile_fur_verschiedene_Haushaltstypen

Parameters **df_census_households_nuts1** (*pd.DataFrame*) – census household data on NUTS-1 level in absolute values

Returns **df_dist_households** (*pd.DataFrame*) – Distribution of households type

`set_multiindex_to_profiles`(*hh_profiles*)
The profile id is split into type and number and set as multiindex.

Parameters **hh_profiles** (*pd.DataFrame*) – Profiles

Returns **hh_profiles** (*pd.DataFrame*) – Profiles with Multiindex

`write_hh_profiles_to_db`(*hh_profiles*)
Write HH demand profiles of IEE into db. One row per profile type. The annual load profile timeseries is an array.

schema: demand tablename: iee_household_load_profiles

Parameters **hh_profiles** (*pd.DataFrame*) – It is meant to be used with `df.applymap()`

`write_refinded_households_to_db`(*df_census_households_grid_refined*)

mapping

`class EgonMapZensusMvgdBuildings`(***kwargs*)
Bases: `sqlalchemy.ext.declarative.api.Base`

A final mapping table including all buildings used for residential and cts, heat and electricity timeseries. Including census cells, mvgd bus_id, building type (osm or synthetic)

building_id

bus_id

electricity

heat

osm

sector

zensus_population_id

`map_all_used_buildings`()
This function maps all used buildings from OSM and synthetic ones.

tools

psql_insert_copy(*table*, *conn*, *keys*, *data_iter*)
Execute SQL statement inserting data

Parameters

- **table** (*pandas.io.sql.SQLTable*)
- **conn** (*sqlalchemy.engine.Engine or sqlalchemy.engine.Connection*)
- **keys** (*list of str*) – Column names
- **data_iter** (*Iterable that iterates the values to be inserted*)

random_ints_until_sum(*s_sum*, *m_max*)
Generate non-negative random integers < *m_max* summing to *s_sum*.

random_point_in_square(*geom*, *tol*)
Generate a random point within a square

Parameters

- **geom** (*gpd.Series*) – Geometries of square
- **tol** (*float*) – tolerance to square bounds

Returns **points** (*gpd.Series*) – Series of random points

specific_int_until_sum(*s_sum*, *i_int*)
Generate list *i_int* summing to *s_sum*. Last value will be <= *i_int*

timeit(*func*)
Decorator for measuring function's running time.

write_table_to_postgis(*gdf*, *table*, *engine=Engine(postgresql+psycopg2://egon:***@127.0.0.1:59734/egon-data)*, *drop=True*)
Helper function to append df data to table in db. Only predefined columns are passed. Error will raise if column is missing. Dtype of columns are taken from table definition.

Parameters

- **gdf** (*gpd.DataFrame*) – Table of data
- **table** (*declarative_base*) – Metadata of db table to export to
- **engine** – connection to database db.engine()
- **drop** (*bool*) – Drop table before appending

write_table_to_postgres(*df*, *db_table*, *drop=False*, *index=False*, *if_exists='append'*)
Helper function to append df data to table in db. Fast string-copy is used. Only predefined columns are passed. If column is missing in dataframe a warning is logged. Dtypes of columns are taken from table definition. The writing process happens in a scoped session.

Parameters

- **df** (*pd.DataFrame*) – Table of data
- **db_table** (*declarative_base*) – Metadata of db table to export to
- **drop** (*boolean, default False*) – Drop db-table before appending
- **index** (*boolean, default False*) – Write DataFrame index as a column.
- **if_exists** (*{'fail', 'replace', 'append'}, default 'append'*) –

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

10.5.36 emobility

heavy_duty_transport

create_h2_buses

Map demand to H2 buses and write to DB.

assign_h2_buses(*scenario: str = 'eGon2035'*)

delete_old_entries(*scenario: str*)
Delete loads and load timeseries.

Parameters **scenario** (*str*) – Name of the scenario.

insert_hgv_h2_demand()
Insert list of hgv H2 demand (one per NUTS3) in database.

insert_new_entries(*hgv_h2_demand_gdf: geopandas.geodataframe.GeoDataFrame*)
Insert loads.

Parameters **hgv_h2_demand_gdf** (*geopandas.GeoDataFrame*) – Load data to insert.

kg_per_year_to_mega_watt(*df: pd.DataFrame | gpd.GeoDataFrame*)

read_hgv_h2_demand(*scenario: str = 'eGon2035'*)

data_io

Read data from DB and download.

bast_gdf()
Reads BAST data.

boundary_gdf()
Get outer boundary from database.

get_data()
Load all necessary data.

nuts3_gdf()
Read in NUTS3 geo shapes.

db_classes

DB tables / SQLAlchemy ORM classes for heavy duty transport.

class EgonHeavyDutyTransportVoronoi(***kwargs*)
Bases: `sqlalchemy.ext.declarative.api.Base`

Class definition of table demand.egon_heavy_duty_transport_voronoi.

area

geometry

hydrogen_consumption

normalized_truck_traffic

nuts3

scenario

truck_traffic

h2_demand_distribution

Calculation of hydrogen demand based on a Voronoi partition of counted truck traffic used to allocate it to NUTS3 regions and finally aggregate it on NUTS3 level.

calculate_total_hydrogen_consumption(*scenario: str = 'eGon2035'*)
Calculate the total hydrogen demand for trucking in Germany.

geo_intersect(*voronoi_gdf: geopandas.geodataframe.GeoDataFrame*, *nuts3_gdf: geopandas.geodataframe.GeoDataFrame*, *mode: str = 'intersection'*)
Calculate Intersections between two GeoDataFrames and distribute truck traffic

run_egon_truck()

voronoi(*points: geopandas.geodataframe.GeoDataFrame*, *boundary: geopandas.geodataframe.GeoDataFrame*)
Building a Voronoi Field from points and a boundary.

Main module for preparation of model data (static and timeseries) for heavy duty transport.

Contents of this module

- Creation of DB tables
- Download and preprocessing of vehicle registration data from BAST
- Calculation of hydrogen demand based on a Voronoi distribution of counted truck traffic among NUTS 3 regions.
- Writing results to DB
- Mapping demand to H2 buses and writing to DB

class HeavyDutyTransport(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Class for preparation of static and timeseries data for heavy duty transport.

Dependencies

- *Vg250*
- *EtragoSetup*
- *GasAreaseGon2035*

Resulting tables

- *demand.egon_heavy_duty_transport_voronoi* is created and filled
- *grid.egon_etrago_load* is extended
- *grid.egon_etrago_load_timeseries* is extended

Configuration

The config of this dataset can be found in *datasets.yml* in section *mobility_hgv*.

Scenarios and variations

Assumptions can be changed within the *datasets.yml*.

In the context of the eGon project, it is assumed that e-trucks will be completely hydrogen-powered and in both scenarios the hydrogen consumption is assumed to be 6.68 kg H2 per 100 km with an additional supply chain leakage rate of 0.5 %.

Scenario NEP C 2035

The ramp-up figures are taken from Scenario C 2035 Grid Development Plan 2021-2035. According to this, 100,000 e-trucks are expected in Germany in 2035, each covering an average of 100,000 km per year. In total this means 10 billion km.

Scenario eGon100RE

In the case of the eGon100RE scenario it is assumed that the HGV traffic is completely hydrogen-powered. The total freight traffic with 40 Billion km is taken from the BMWK Langfristszenarien GHG-emission free scenarios (SNF > 12 t zGG).

Methodology

Using a Voronoi interpolation, the censuses of the BASt data is distributed according to the area fractions of the Voronoi fields within each mv grid or any other geometries like NUTS-3.

name: str = 'HeavyDutyTransport'

version: str = '0.0.2'

create_tables()
Drops existing *demand.egon_heavy_duty_transport_voronoi* is extended table and creates new one.

download_hgv_data()
Downloads BAST data.

The data is downloaded to file specified in *datasets.yml* in section *mobility_hgv/original_data/sources/BAST/file*.

motorized_individual_travel

db_classes

DB tables / SQLAlchemy ORM classes for motorized individual travel

class EgonEvCountMunicipality(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_ev_count_municipality.

Contains electric vehicle counts per municipality.

ags

bev_luxury

bev_medium

bev_mini

phev_luxury

phev_medium

phev_mini

rs7_id

scenario

scenario_variation

class EgonEvCountMvGridDistrict(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_ev_count_mv_grid_district.

Contains electric vehicle counts per MV grid district.

bev_luxury

bev_medium

bev_mini

bus_id

phev_luxury

phev_medium

phev_mini

rs7_id

scenario

scenario_variation

class EgonEvCountRegistrationDistrict(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_ev_count_registration_district.

Contains electric vehicle counts per registration district.

ags_reg_district

bev_luxury

bev_medium

bev_mini

phev_luxury

phev_medium

phev_mini

reg_district

scenario

scenario_variation

class EgonEvMetadata(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_ev_metadata.

Contains EV Pool Metadata.

end_date

eta_cp

grid_timeseries

grid_timeseries_by_usecase

scenario

soc_min

start_date

stepsize

class EgonEvMvGridDistrict(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_ev_mv_grid_district.

Contains list of electric vehicles per MV grid district.

bus_id

egon_ev_pool_ev_id

id

scenario

scenario_variation

class EgonEvPool(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_ev_pool.

Each row is one EV, uniquely defined by either (*ev_id*) or (*rs7_id*, *type*, *simbev_id*).

ev_id: Unique id of EV

rs7_id: id of RegioStar7 region

type:

type of EV, one of

- bev_mini
- bev_medium
- bev_luxury
- phev_mini
- phev_medium
- phev_luxury

simbev_ev_id: id of EV as exported by simBEV

ev_id

rs7_id

scenario

simbev_ev_id

type

class EgonEvTrip(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table demand.egon_ev_trip.

Each row is one event of a specific electric vehicle which is uniquely defined by *rs7_id*, *ev_id* and *event_id*.

scenario: Scenario

event_id: Unique id of EV event

egon_ev_pool_ev_id: id of EV, references EgonEvPool.ev_id

simbev_event_id: id of EV event, unique within a specific EV dataset

location:

Location of EV event, one of

- "0_work"
- "1_business"
- "2_school"
- "3_shopping"
- "4_private/ridesharing"
- "5_leisure"
- "6_home"
- "7_charging_hub"
- "driving"

use_case:

Use case of EV event, one of

- "public" (public charging)
- "home" (private charging at 6_home)
- "work" (private charging at 0_work)
- <empty> (driving events)

charging_capacity_nominal: Nominal charging capacity in kW

charging_capacity_grid: Charging capacity at grid side in kW, includes efficiency of charging infrastructure

charging_capacity_battery: Charging capacity at battery side in kW, includes efficiency of car charger

soc_start: State of charge at start of event

soc_start: State of charge at end of event

charging_demand: Energy demand during parking/charging event in kWh. 0 if no charging takes place.

park_start: Start timestep of parking event (15min interval, e.g. 4 = 1h)

park_end: End timestep of parking event (15min interval)

drive_start: Start timestep of driving event (15min interval)

drive_end: End timestep of driving event (15min interval)

consumption: Energy demand during driving event in kWh

Notes

pgSQL's REAL is sufficient for floats as simBEV rounds output to 4 digits.

`charging_capacity_battery`

`charging_capacity_grid`

`charging_capacity_nominal`

`charging_demand`

`consumption`

`drive_end`

`drive_start`

`egon_ev_pool_ev_id`

`event_id`

`location`

`park_end`

`park_start`

`scenario`

`simbev_event_id`

`soc_end`

`soc_start`

`use_case`

ev_allocation

- Calculate number of electric vehicles and allocate on different spatial levels: *allocate_evs_numbers()*
- Allocate specific EVs to MV grid districts: *allocate_evs_to_grid_districts()*

`allocate_evs_numbers`()
Allocate electric vehicles to different spatial levels.

Accocation uses today's vehicles registration data per registration district from KBA and scales scenario's EV targets (BEV and PHEV) linearly using population. Furthermore, a RegioStaR7 code (BMVI) is assigned.

Levels: * districts of registration * municipalities * grid districts

`allocate_evs_to_grid_districts`()
Allocate EVs to MV grid districts for all scenarios and scenario variations.

Each grid district in egon.data.datasets.mv_grid_districts.MvGridDistricts is assigned a list of electric vehicles from the EV pool in EgonEvPool based on the RegioStar7 region and the counts per EV type in EgonEvCountMvGridDistrict. Results are written to EgonEvMvGridDistrict.

calc_evs_per_grid_district(*ev_data_muns*)
Calculate EVs per grid district by using population weighting

Parameters **ev_data_muns** (*pandas.DataFrame*) – EV data for municipalities

Returns *pandas.DataFrame* – EV data for grid districts

calc_evs_per_municipality(*ev_data*, *rs7_data*)
Calculate EVs per municipality

Parameters

- **ev_data** (*pandas.DataFrame*) – EVs per regstration district
- **rs7_data** (*pandas.DataFrame*) – RegioStaR7 data

calc_evs_per_reg_district(*scenario_variation_parameters*, *kba_data*)
Calculate EVs per registration district

Parameters

- **scenario_variation_parameters** (*dict*) – Parameters of scenario variation
- **kba_data** (*pandas.DataFrame*) – Vehicle registration data for registration district

Returns *pandas.DataFrame* – EVs per registration district

fix_missing_ags_municipality_regiostar(*muns*, *rs7_data*)
Check if all AGS of municipality dataset are included in RegioStaR7 dataset and vice versa.

As of Dec 2021, some municipalities are not included int the RegioStaR7 dataset. This is mostly caused by incorporations of a municipality by another municipality. This is fixed by assigning a RS7 id from another municipality with similar AGS (most likely a neighboured one).

Missing entries in the municipality dataset is printed but not fixed as it doesn't result in bad data. Nevertheless, consider to update the municipality/VG250 dataset.

Parameters

- **muns** (*pandas.DataFrame*) – Municipality data
- **rs7_data** (*pandas.DataFrame*) – RegioStaR7 data

Returns *pandas.DataFrame* – Fixed RegioStaR7 data

helpers

Helpers: constants and functions for motorized individual travel

read_kba_data()
Read KBA data from CSV

read_rs7_data()
Read RegioStaR7 data from CSV

read_simbev_metadata_file(*scenario_name*, *section*)
Read metadata of simBEV run

Parameters

- **scenario_name** (*str*) – Scenario name

- **section** (*str*) – Metadata section to be returned, one of * “tech_data” * “charge_prob_slow” * “charge_prob_fast”

Returns *pd.DataFrame* – Config data

reduce_mem_usage(*df: pandas.core.frame.DataFrame*, *show_reduction: bool = False*) → pandas.core.frame.DataFrame

Function to automatically check if columns of a pandas DataFrame can be reduced to a smaller data type. Source: https://www.mikulskibartosz.name/how-to-reduce-memory-usage-in-pandas/

Parameters

- **df** (*pd.DataFrame*) – DataFrame to reduce memory usage on
- **show_reduction** (*bool*) – If True, print amount of memory reduced

Returns *pd.DataFrame* – DataFrame with memory usage decreased

model_timeseries

Generate timeseries for eTraGo and pypsa-eur-sec

Call order

- generate_model_data_eGon2035() / generate_model_data_eGon100RE() * generate_model_data()
  - generate_model_data_grid_district() * load_evs_trips() * data_preprocessing() * generate_load_time_series() * write_model_data_to_db()

Notes

TODO REWORK Share of EV with access to private charging infrastructure (*flex_share*) for use cases work and home are not supported by simBEV v0.1.2 and are applied here (after simulation). Applying those fixed shares post-simulation introduces small errors compared to application during simBEV's trip generation.

Values (cf. *flex_share* in scenario parameters *egon.data.datasets.scenario_parameters.parameters.mobility()*) were linearly extrapolated based upon https://nationale-leitstelle.de/wp-content/pdf/broschuere-lis-2025-2030-final.pdf (p.92): * eGon2035: home=0.8, work=1.0 * eGon100RE: home=1.0, work=1.0

data_preprocessing(*scenario_data: pandas.core.frame.DataFrame*, *ev_data_df: pandas.core.frame.DataFrame*) → pandas.core.frame.DataFrame

Filter SimBEV data to match region requirements. Duplicates profiles if necessary. Pre-calculates necessary parameters for the load time series.

Parameters

- **scenario_data** (*pd.Dataframe*) – EV per grid district
- **ev_data_df** (*pd.Dataframe*) – Trip data

Returns *pd.Dataframe* – Trip data

delete_model_data_from_db()

Delete all eMob MIT data from eTraGo PF tables

generate_load_time_series(*ev_data_df: pandas.core.frame.DataFrame*, *run_config: pandas.core.frame.DataFrame*, *scenario_data: pandas.core.frame.DataFrame*) → pandas.core.frame.DataFrame

Calculate the load time series from the given trip data. A dumb charging strategy is assumed where each EV starts charging immediately after plugging it in. Simultaneously the flexible charging capacity is calculated.

Parameters

- **ev_data_df** (*pd.DataFrame*) – Full trip data
- **run_config** (*pd.DataFrame*) – simBEV metadata: run config
- **scenario_data** (*pd.Dataframe*) – EV per grid district

Returns *pd.DataFrame* – time series of the load and the flex potential

`generate_model_data_bunch`(*scenario_name: str*, *bunch: range*) → None

Generates timeseries from simBEV trip data for a bunch of MV grid districts.

Parameters

- **scenario_name** (*str*) – Scenario name
- **bunch** (*list*) – Bunch of grid districts to generate data for, e.g. [1,2,..,100]. Note: *bunch* is NOT a list of grid districts but is used for slicing the ordered list (by bus_id) of grid districts! This is used for parallelization. See `egon.data.datasets.emobility.motorized_individual_travel.MotorizedIndividualTravel.generate_model_data_tasks()`

`generate_model_data_eGon100RE_remaining`()

Generates timeseries for eGon100RE scenario for grid districts which has not been processed in the parallel tasks before.

`generate_model_data_eGon2035_remaining`()

Generates timeseries for eGon2035 scenario for grid districts which has not been processed in the parallel tasks before.

`generate_model_data_grid_district`(*scenario_name: str*, *evs_grid_district: pandas.core.frame.DataFrame*, *bat_cap_dict: dict*, *run_config: pandas.core.frame.DataFrame*) → tuple

Generates timeseries from simBEV trip data for MV grid district

Parameters

- **scenario_name** (*str*) – Scenario name
- **evs_grid_district** (*pd.DataFrame*) – EV data for grid district
- **bat_cap_dict** (*dict*) – Battery capacity per EV type
- **run_config** (*pd.DataFrame*) – simBEV metadata: run config

Returns *pd.DataFrame* – Model data for grid district

`generate_static_params`(*ev_data_df: pandas.core.frame.DataFrame*, *load_time_series_df: pandas.core.frame.DataFrame*, *evs_grid_district_df: pandas.core.frame.DataFrame*) → dict

Calculate static parameters from trip data.

- cumulative initial SoC
- cumulative battery capacity
- simultaneous plugged in charging capacity

Parameters **ev_data_df** (*pd.DataFrame*) – Fill trip data

Returns *dict* – Static parameters

`load_evs_trips`(*scenario_name: str*, *evs_ids: list*, *charging_events_only: bool = False*, *flex_only_at_charging_events: bool = True*) → pandas.core.frame.DataFrame

Load trips for EVs

Parameters

- **scenario_name** (*str*) – Scenario name
- **evs_ids** (*list of int*) – IDs of EV to load the trips for
- **charging_events_only** (*bool*) – Load only events where charging takes place
- **flex_only_at_charging_events** (*bool*) – Flexibility only at charging events. If False, flexibility is provided by plugged-in EVs even if no charging takes place.

Returns *pd.DataFrame* – Trip data

`load_grid_district_ids()` → pandas.core.series.Series
Load bus IDs of all grid districts

`write_model_data_to_db(static_params_dict: dict, load_time_series_df: pandas.core.frame.DataFrame, bus_id: int, scenario_name: str, run_config: pandas.core.frame.DataFrame, bat_cap: pandas.core.frame.DataFrame)` → None
Write all results for grid district to database

Parameters

- **static_params_dict** (*dict*) – Static model params
- **load_time_series_df** (*pd.DataFrame*) – Load time series for grid district
- **bus_id** (*int*) – ID of grid district
- **scenario_name** (*str*) – Scenario name
- **run_config** (*pd.DataFrame*) – simBEV metadata: run config
- **bat_cap** (*pd.DataFrame*) – Battery capacities per EV type

Returns *None*

tests

Sanity checks for motorized individual travel

`validate_electric_vehicles_numbers(dataset_name, ev_data, ev_target)`
Validate cumulative numbers of electric vehicles' distribution.

Tests * Check if all cells are not NaN * Check if total number matches produced results (tolerance: 0.01 %)

Parameters

- **dataset_name** (*str*) – Name of data, used for error printing
- **ev_data** (*pd.DataFrame*) – EV data
- **ev_target** (*int*) – Desired number of EVs

Main module for preparation of model data (static and timeseries) for motorized individual travel (MIT).

Contents of this module

- Creation of DB tables
- Download and preprocessing of vehicle registration data from KBA and BMVI
- Calculate number of electric vehicles and allocate on different spatial levels.
- Extract and write pre-generated trips to DB

class MotorizedIndividualTravel(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Class to set up static and timeseries data for motorized individual travel (MIT).

For more information see data documentation on mobility-demand-mit-ref.

Dependencies

- *DataBundle*
- *MvGridDistricts*
- *ScenarioParameters*
- *EtragoSetup*
- *ZensusMvGridDistricts*
- *ZensusVg250*
- *StorageEtrago*
- *HtsEtragoTable*
- *ChpEtrago*
- *DsmPotential*
- *HeatEtrago*
- *Egon_etrago_gen*
- *OpenCycleGasTurbineEtrago*
- *HydrogenStoreEtrago*
- *HydrogenPowerLinkEtrago*
- *HydrogenMethaneLinkEtrago*
- *GasAreaseGon100RE*
- *CH4Production*
- *CH4Storages*

Resulting Tables

- *EgonEvPool* is created and filled
- *EgonEvTrip* is created and filled
- *EgonEvCountRegistrationDistrict* is created and filled
- *EgonEvCountMunicipality* is created and filled
- *EgonEvCountMvGridDistrict* is created and filled
- *EgonEvMvGridDistrict* is created and filled
- *EgonEvMetadata* is created and filled

Configuration

The config of this dataset can be found in *datasets.yml* in section *emobility_mit*.

name: str = 'MotorizedIndividualTravel'

version: str = '0.0.7'

adapt_numpy_float64(*numpy_float64*)

adapt_numpy_int64(*numpy_int64*)

create_tables()
Create tables for electric vehicles

Returns *None*

download_and_preprocess()
Downloads and preprocesses data from KBA and BMVI

Returns

- *pandas.DataFrame* – Vehicle registration data for registration district
- *pandas.DataFrame* – RegioStaR7 data

extract_trip_file()
Extract trip file from data bundle

write_evs_trips_to_db()
Write EVs and trips generated by simBEV from data bundle to database table

write_metadata_to_db()
Write used SimBEV metadata per scenario to database.

motorized_individual_travel_charging_infrastructure

db_classes

DB tables / SQLAlchemy ORM classes for charging infrastructure

class EgonEmobChargingInfrastructure(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table grid.egon_emob_charging_infrastructure.

cp_id

geometry

mv_grid_id

use_case

weight

infrastructure_allocation

The charging infrastructure allocation is based on [TracBEV[(https://github.com/rl-institut/tracbev). TracBEV is a tool for the regional allocation of charging infrastructure. In practice this allows users to use results generated via [SimBEV](https://github.com/rl-institut/simbev) and place the corresponding charging points on a map. These are split into the four use cases hpc, public, home and work.

get_data() → dict[gpd.GeoDataFrame]
Load all data necessary for TracBEV. Data loaded:

- 'hpc_positions' - Potential hpc positions
- 'landuse' - Potential work related positions

- 'poi_cluster' - Potential public related positions
- 'public_positions' - Potential public related positions
- 'housing_data' - Potential home related positions loaded from DB
- 'boundaries' - MV grid boundaries
- miscellaneous found in *datasets.yml* in section *charging_infrastructure*

run_tracbev()
Wrapper function to run charging infrastructure allocation

run_tracbev_potential(*data_dict: dict*) → None
Main function to run TracBEV in potential (determination of all potential charging points).

Parameters **data_dict** (*dict*) – Data dict containing all TracBEV run information

run_use_cases(*data_dict: dict*) → None
Run all use cases

Parameters **data_dict** (*dict*) – Data dict containing all TracBEV run information

write_to_db(*gdf: gpd.GeoDataFrame*, *mv_grid_id: int | float*, *use_case: str*) → None
Write results to charging infrastructure DB table

Parameters

- **gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame to save
- **mv_grid_id** (*int or float*) – MV grid ID corresponding to the data
- **use_case** (*str*) – Calculated use case

use_cases

Functions related to the four different use cases

apportion_home(*home_df: pandas.core.frame.DataFrame*, *num_spots: int*, *config: dict*)

distribute_by_poi(*region_poi: gpd.GeoDataFrame*, *num_points: int | float*)

home(*home_data: geopandas.geodataframe.GeoDataFrame*, *uc_dict: dict*) →
geopandas.geodataframe.GeoDataFrame
Calculate placements and energy distribution for use case hpc.

Parameters

- **home_data** – gpd.GeoDataFrame info about house types
- **uc_dict** – dict contains basic run info like region boundary and save directory

home_charge_spots(*house_array: pd.Series | np.array*, *config: dict*)

hpc(*hpc_points: geopandas.geodataframe.GeoDataFrame*, *uc_dict: dict*) →
geopandas.geodataframe.GeoDataFrame
Calculate placements and energy distribution for use case hpc.

Parameters

- **hpc_points** – gpd.GeoDataFrame GeoDataFrame of possible hpc locations
- **uc_dict** – dict contains basic run info like region boundary and save directory

match_existing_points(*region_points: geopandas.geodataframe.GeoDataFrame*, *region_poi: geopandas.geodataframe.GeoDataFrame*)

public(*public_points: geopandas.geodataframe.GeoDataFrame*, *public_data: geopandas.geodataframe.GeoDataFrame*, *uc_dict: dict*) → geopandas.geodataframe.GeoDataFrame
Calculate placements and energy distribution for use case hpc.

Parameters

- **public_points** – gpd.GeoDataFrame existing public charging points
- **public_data** – gpd.GeoDataFrame clustered POI
- **uc_dict** – dict contains basic run info like region boundary and save directory

work(*landuse: geopandas.geodataframe.GeoDataFrame*, *weights_dict: dict*, *uc_dict: dict*) → geopandas.geodataframe.GeoDataFrame
Calculate placements and energy distribution for use case hpc.

Parameters

- **landuse** – gpd.GeoDataFrame work areas by land use
- **weights_dict** – dict weights for different land use types
- **uc_dict** – dict contains basic run info like region boundary and save directory

Motorized Individual Travel (MIT) Charging Infrastructure

Main module for preparation of static model data for charging infrastructure for motorized individual travel.

class MITChargingInfrastructure(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Preparation of static model data for charging infrastructure for motorized individual travel.

The following is done:

- Creation of DB tables
- Download and preprocessing of vehicle registration data from zenodo
- Determination of all potential charging locations for the four charging use cases home, work, public and hpc per MV grid district
- Write results to DB

Dependencies

- *MvGridDistricts*
- *map_houseprofiles_to_buildings*

Resulting tables

- *grid.egon_emob_charging_infrastructure* is created and filled

Configuration

The config of this dataset can be found in *datasets.yml* in section *charging_infrastructure*.

Charging Infrastructure

The charging infrastructure allocation is based on TracBEV. TracBEV is a tool for the regional allocation of charging infrastructure. In practice this allows users to use results generated via SimBEV and place the corresponding charging points on a map. These are split into the four use cases home, work, public and hpc.

name: `str = 'MITChargingInfrastructure'`

version: `str = '0.0.1'`

create_tables() → None
Create tables for charging infrastructure

Returns *None*

download_zip(*url: str*, *target: Path*, *chunk_size: int | None = 128*) → None
Download zip file from URL.

Parameters

- **url** (*str*) – URL to download the zip file from
- **target** (*pathlib.Path*) – Directory to save zip to
- **chunk_size** (*int or None*) – Size of chunks to download

get_tracbev_data() → None
Wrapper function to get TracBEV data provided on Zenodo.

unzip_file(*source: pathlib.Path*, *target: pathlib.Path*) → None
Unzip zip file

Parameters

- **source** (*Path*) – Zip file path to unzip
- **target** (*Path*) – Directory to save unzipped content to

10.5.37 gas_neighbours

eGon100RE

Module containing code dealing with cross border gas pipelines for eGon100RE

In this module the cross border pipelines for H2 and CH4, exclusively between Germany and its neighbouring countries, in eGon100RE are defined and inserted in the database.

Dependecies (pipeline)

- **dataset** PypsaEurSec, GasNodesandPipes, HydrogenBusEtrago, ElectricalNeighbours

Resulting tables

- grid.egon_etrago_link is completed

calculate_crossbordering_gas_grid_capacities_eGon100RE(*cap_DE*, *DE_pipe_capacities_list*)
Attribute gas cross border grid capacities for eGon100RE

This function attributes to each cross border pipeline (H2 and CH4) between Germany and its neighbouring countries its capacity.

Parameters

- **cap_DE** (*pandas.DataFrame*) – List of the H2 and CH4 exchange capacity for each neighbouring country of Germany.

- **DE_pipe_capacities_list** (*pandas.DataFrame*) – List of the cross border for H2 and CH4 pipelines between Germany and its neighbouring countries in eGon100RE, with geometry (geom and topo) but no capacity.

Returns **Crossbordering_pipe_capacities_list** (*pandas.DataFrame*) – List of the cross border H2 and CH4 pipelines between Germany and its neighbouring countries in eGon100RE.

define_DE_crossbording_pipes_geom_eGon100RE(*scn_name='eGon100RE'*)

Define the missing cross border gas pipelines in eGon100RE

This function defines the cross border pipelines (for H2 and CH4) between Germany and its neighbouring countries. These pipelines are defined as links and there are copied from the corresponding CH4 cross border pipelines from eGon2035.

Parameters **scn_name** (*str*) – Name of the scenario

Returns **gas_pipelines_list_DE** (*pandas.DataFrame*) – List of the cross border H2 and CH4 pipelines between Germany and its neighbouring countries in eGon100RE, with geometry (geom and topo) but no capacity.

insert_gas_neigbours_eGon100RE()

Insert missing gas cross border grid capacities for eGon100RE

This function insert the cross border pipelines for H2 and CH4, exclusively between Germany and its neighbouring countries, for eGon100RE in the database by executing the following steps:

- call of the function *define_DE_crossbording_pipes_geom_eGon100RE()*, that defines the cross border pipelines (H2 and CH4) between Germany and its neighbouring countries
- call of the function *read_DE_crossbordering_cap_from_pes()*, that calculates the cross border total exchange capactities for H2 and CH4 between Germany and its neighbouring countries based on the pypsa-eur-sec results
- call of the function *calculate_crossbordering_gas_grid_capacities_eGon100RE()*, that attributes to each cross border pipeline (H2 and CH4) between Germany and its neighbouring countries its capacity
- insertion of the H2 and CH4 pipelines between Germany and its neighbouring countries in the database with function `insert_gas_grid_capacities()`

Returns *None*

read_DE_crossbordering_cap_from_pes()

Read gas pipelines cross border capacities from pes run

This function calculates the cross border total exchange capactities for H2 and CH4 between Germany and its neighbouring countries based on the pypsa-eur-sec results.

Returns **DE_pipe_capacities_list** (*pandas.DataFrame*) – List of the H2 and CH4 exchange capacity for each neighbouring country of Germany.

eGon2035

Central module containing code dealing with gas neighbours for eGon2035

`calc_capacities()`
Calculates gas production capacities of neighbouring countries

For each neigbouring country, this function calculates the gas generation capacity in 2035 using the function *calc_capacity_per_year()* for 2030 and 2040 and interpolates the results. These capacities include LNG import, as well as conventional and biogas production. Two conventional gas generators are added for Norway and Russia interpolating the supply potential values from the TYNPD 2020 for 2030 and 2040.

Returns **grouped_capacities** (*pandas.DataFrame*) – Gas production capacities per foreign node

`calc_capacity_per_year(df, lng, year)`
Calculates gas production capacities for a specified year

For a specified year and for the foreign country nodes this function calculates the gas production capacities, considering the gas (conventional and bio) production capacities from TYNDP data and the LNG import capacities from Scigrid gas data.

The columns of the returned dataframe are the following:

- Value_bio_year: biogas production capacity (in GWh/d)
- Value_conv_year: conventional gas production capacity including LNG imports (in GWh/d)
- CH4_year: total gas production capacity (in GWh/d). This value is calculated using the peak production value from the TYNDP.
- e_nom_max_year: total gas production capacity representative for the whole year (in GWh/d). This value is calculated using the average production value from the TYNDP and will then be used to limit the energy that can be generated in one year.
- share_LNG_year: share of LGN import capacity in the total gas production capacity
- share_conv_pipe_year: share of conventional gas extraction capacity in the total gas production capacity
- share_bio_year: share of biogas production capacity in the total gas production capacity

Parameters

- **df** (*pandas.DataFrame*) – Gas (conventional and bio) production capacities from TYNDP (in GWh/d)
- **lng** (*pandas.Series*) – LNG terminal capacities per foreign country node (in GWh/d)
- **year** (*int*) – Year to calculate gas production capacities for

Returns **df_year** (*pandas.DataFrame*) – Gas production capacities (in GWh/d) per foreign country node

`calc_ch4_storage_capacities()`
Calculate CH4 storage capacities for neighboring countries

Returns

- **ch4_storage_capacities** (*pandas.DataFrame*)
- *Methane gas storage capacities per country in MWh*

calc_global_ch4_demand(*Norway_global_demand_1y*)
Calculates global CH4 demands abroad for eGon2035 scenario

The data comes from TYNDP 2020 according to NEP 2021 from the scenario 'Distributed Energy'; linear interpolates between 2030 and 2040.

Returns *pandas.DataFrame* – Global (yearly) CH4 final demand per foreign node

calc_global_power_to_h2_demand()
Calculate H2 demand abroad for eGon2035 scenario

Calculates global power demand abroad linked to H2 production. The data comes from TYNDP 2020 according to NEP 2021 from the scenario 'Distributed Energy'; linear interpolate between 2030 and 2040.

Returns **global_power_to_h2_demand** (*pandas.DataFrame*) – Global hourly power-to-h2 demand per foreign node

calculate_ch4_grid_capacities()
Calculates CH4 grid capacities for foreign countries based on TYNDP-data

Returns **Neighbouring_pipe_capacities_list** (*pandas.DataFrame*) – Table containing the CH4 grid capacity for each foreign country

calculate_ocgt_capacities()
Calculate gas turbine capacities abroad for eGon2035

Calculate gas turbine capacities abroad for eGon2035 based on TYNDP 2020, scenario "Distributed Energy"; interpolated between 2030 and 2040

Returns **df_ocgt** (*pandas.DataFrame*) – Gas turbine capacities per foreign node

get_foreign_gas_bus_id(*carrier='CH4'*)
Calculate the etrago bus id based on the geometry

Map node_ids from TYNDP and etragos bus_id

Parameters **carrier** (*str*) – Name of the carrier

Returns *pandas.Series* – List of mapped node_ids from TYNDP and etragos bus_id

grid()
Insert data from TYNDP 2020 according to NEP 2021 Scenario 'Distributed Energy; linear interpolate between 2030 and 2040

Returns *None*

import_ch4_demandTS()
Calculate global CH4 demand in Norway and CH4 demand profile

Import from the PyPSA-eur-sec run the time series of residential rural heat per neighbor country. This time series is used to calculate:

- the global (yearly) heat demand of Norway (that will be supplied by CH4)
- the normalized CH4 hourly resolved demand profile

Returns

- **Norway_global_demand** (*Float*) – Yearly heat demand of Norway in MWh
- **neighbor_loads_t** (*pandas.DataFrame*) – Normalized CH4 hourly resolved demand profiles per neighbor country

insert_ch4_demand(*global_demand*, *normalized_ch4_demandTS*)
Insert CH4 demands abroad into the database for eGon2035

Parameters

- **global_demand** (*pandas.DataFrame*) – Global CH4 demand per foreign node in 1 year
- **gas_demandTS** (*pandas.DataFrame*) – Normalized time series of the demand per foreign country

Returns *None*

`insert_generators`(*gen*)
Insert gas generators for foreign countries into the database

Insert gas generators for foreign countries into the database. The marginal cost of the methane is calculated as the sum of the imported LNG cost, the conventional natural gas cost and the biomethane cost, weighted by their share in the total import/ production capacity. LNG gas is considered to be 30% more expensive than the natural gas transported by pipelines (source: iwd, 2022).

Parameters **gen** (*pandas.DataFrame*) – Gas production capacities per foreign node and energy carrier

Returns *None*

`insert_ocgt_abroad`()
Insert gas turbine capacities abroad for eGon2035 in the database

Parameters **df_ocgt** (*pandas.DataFrame*) – Gas turbine capacities per foreign node

Returns *None*

`insert_power_to_h2_demand`(*global_power_to_h2_demand*)
Insert H2 demands into database for eGon2035

Parameters **global_power_to_h2_demand** (*pandas.DataFrame*) – Global hourly power-to-h2 demand per foreign node

Returns *None*

`insert_storage`(*ch4_storage_capacities*)
Insert CH4 storage capacities into the database for eGon2035

Parameters **ch4_storage_capacities** (*pandas.DataFrame*) – Methane gas storage capacities per country in MWh

Returns *None*

`read_LNG_capacities`()
Read LNG import capacities from Scigrid gas data

Returns **IGGIELGN_LNGs** (*pandas.Series*) – LNG terminal capacities per foreign country node (in GWh/d)

`tyndp_gas_demand`()
Insert gas demands abroad for eGon2035

Insert CH4 and H2 demands abroad for eGon2035 by executing the following steps:

- **CH4**
  - Calculation of the global CH4 demand in Norway and the CH4 demand profile by executing the function *import_ch4_demandTS()*
  - Calculation of the global CH4 demands by executing the function *calc_global_ch4_demand()*
  - Insertion of the CH4 loads and their associated time series in the database by executing the function *insert_ch4_demand()*

- **H2**
  - Calculation of the global power demand abroad linked to H2 production by executing the function *calc_global_power_to_h2_demand()*
  - Insertion of these loads in the database by executing the function *insert_power_to_h2_demand()*

Returns *None*

tyndp_gas_generation()
Insert data from TYNDP 2020 according to NEP 2021 Scenario 'Distributed Energy'; linear interpolate between 2030 and 2040

Returns *None*

gas_abroad

Module containing functions to insert gas abroad

In this module, functions used to insert the gas components (H2 and CH4) abroad for eGon2035 and eGon100RE are defined.

insert_gas_grid_capacities(*Neighbouring_pipe_capacities_list*, *scn_name*)
Insert crossbordering gas pipelines into the database

This function inserts a list of crossbordering gas pipelines after cleaning the database. For eGon2035, all the CH4 crossbordering pipelines are inserted (no H2 grid in this scenario). For eGon100RE, only the crossbordering pipelines with Germany are inserted (the other ones are inserted in PypsaEurSec), but in this scenario there are H2 and CH4 pipelines.

Parameters

- **Neighbouring_pipe_capacities_list** (*pandas.DataFrame*) – List of the crossbordering gas pipelines
- **scn_name** (*str*) – Name of the scenario

Returns *None*

The central module containing all code dealing with gas neighbours

class GasNeighbours(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

10.5.38 heat_demand

Central module containing all code dealing with the future heat demand import.

This module obtains the residential and service-sector heat demand data for 2015 from Peta5.0.1, calculates future heat demands and saves them in the database with assigned census cell IDs.

class EgonPetaHeat(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

demand

id

scenario

sector

zensus_population_id

class HeatDemandImport(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Insert the annual heat demand per census cell for each scenario

This dataset downloads the heat demand raster data for private households and CTS from Peta 5.0.1 (https://s-eenergies-open-data-euf.hub.arcgis.com/maps/d7d18b63250240a49eb81db972aa573e/about) and stores it into files in the working directory. The data from Peta 5.0.1 represents the status quo of the year 2015. To model future heat demands, the data is scaled to meet target values from external sources. These target values are defined for each scenario in *ScenarioParameters*.

Dependencies

- *ScenarioParameters*
- *Vg250*
- *ZensusVg250*

Resulting tables

- *demand.egon_peta_heat* is created and filled

name: str = 'heat-demands'

version: str = '0.0.1'

add_metadata()

Writes metadata JSON string into table comment.

adjust_residential_heat_to_zensus(*scenario*)

Adjust residential heat demands to fit to zensus population.

In some cases, Peta assigns residential heat demand to unpopulated cells. This can be caused by the different population data used in Peta or buildings in zenus cells without a population (see `egon.data.importing.zensus.adjust_zensus_misc()`)

Residential heat demand in cells without zensus population is dropped. Residential heat demand in cells with zensus population is scaled to meet the overall residential heat demands.

Parameters **scenario** (*str*) – Name of the scenario.

Returns *None*

cutout_heat_demand_germany()

Save cutouts of Germany's 2015 heat demand densities from Europe-wide tifs.

1. Get the German state boundaries
2. Load the unzip 2015 heat demand data (Peta5_0_1) and
3. Cutout Germany's residential and service-sector heat demand densities
4. Save the cutouts as tiffs

Parameters **None**

Returns *None*

Notes

The alternative of cutting out Germany from the pan-European raster based on German census cells, instead of using state boundaries with low resolution (to avoid inaccuracies), was not implemented in order to achieve consistency with other datasets (e.g. egon_mv_grid_district). Besides, all attempts to read, (union) and load cells from the local database failed, but were documented as commented code within this function and afterwards removed. If you want to have a look at the comments, please check out commit ec3391e182215b32cd8b741557a747118ab61664, which is the last commit still containing them.

Also the usage of a buffer around the boundaries and the subsequent selection of German cells was not implemented. could be used, but then it must be ensured that later only heat demands of cells belonging to Germany are used.

download_peta5_0_1_heat_demands()

Download Peta5.0.1 tiff files.

The downloaded data contain residential and service-sector heat demands per hectar grid cell for 2015.

Parameters **None**

Returns *None*

Notes

The heat demand data in the Peta5.0.1 dataset are assumed not change. An upgrade to a higher Peta version is currently not foreseen. Therefore, for the version management we can assume that the dataset will not change, unless the code is changed.

future_heat_demand_germany(*scenario_name*)

Calculate the future residential and service-sector heat demand per ha.

The calculation is based on Peta5_0_1 heat demand densities, cutout for Germany, for the year 2015. The given scenario name is used to read the adjustment factors for the heat demand rasters from the scenario table.

Parameters **scenario_name** (*str*) – Selected scenario name for which assumptions will be loaded.

Returns *None*

Notes

None

heat_demand_to_db_table()
Import heat demand rasters and convert them to vector data.

Specify the rasters to import as raster file patterns (file type and directory containing raster files, which all will be imported). The rasters are stored in a temporary table called "heat_demand_rasters". The final demand data, having the census IDs as foreign key (from the census population table), are genetated by the provided sql script (raster2cells-and-centroids.sql) and are stored in the table "demand.egon_peta_heat".

Parameters **None**

Returns *None*

Notes

Please note that the data from "demand.egon_peta_heat" is deleted prior to the import, so make sure you're not loosing valuable data.

scenario_data_import()
Call all heat demand import related functions.

This function executes the functions that download, unzip and adjust the heat demand distributions from Peta5.0.1 and that save the future heat demand distributions for Germany as tiffs as well as with census grid IDs as foreign key in the database.

Parameters **None**

Returns *None*

Notes

None

unzip_peta5_0_1_heat_demands()
Unzip the downloaded Peta5.0.1 tiff files.

Parameters **None**

Returns *None*

Notes

It is assumed that the Peta5.0.1 dataset does not change and that the version number does not need to be checked.

10.5.39 heat_demand_timeseries

daily

class EgonDailyHeatDemandPerClimateZone(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

climate_zone

daily_demand_share

day_of_year

temperature_class

class EgonMapZensusClimateZones(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

climate_zone

zensus_population_id

class IdpProfiles(*df_index*, ***kwargs*)
Bases: object

get_temperature_interval(*how='geometric_series'*)
Appoints the corresponding temperature interval to each temperature in the temperature vector.

daily_demand_shares_per_climate_zone()
Calculates shares of heat demand per day for each cliamte zone

Returns *None.*

h_value()
Description: Assignment of daily demand scaling factor to each day of all TRY Climate Zones

Returns **h** (*pandas.DataFrame*) – Hourly factor values for each station corresponding to the temperature profile. Extracted from demandlib.

map_climate_zones_to_zensus()
Geospatial join of zensus cells and climate zones

Returns *None.*

temp_interval()
Description: Create Dataframe with temperature data for TRY Climate Zones :returns: **temperature_interval** (*pandas.DataFrame*) – Hourly temperature intrerval of all 15 TRY Climate station#s temperature profile

temperature_classes()

temperature_profile_extract()
Description: Extract temperature data from atlite :returns: **temperature_profile** (*pandas.DataFrame*) – Temperatur profile of all TRY Climate Zones 2011

idp_pool

class EgonHeatTimeseries(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

building_id

selected_idp_profiles

zensus_population_id

annual_demand_generator()
Description: Create dataframe with annual demand and household count for each zensus cell :returns: **demand_count** (*pandas.DataFrame*) – Annual demand of all zensus cell with MFH and SFH count and

respective associated Station

create()
Description: Create dataframe with all temprature classes, 24hr. profiles and household stock

Returns **idp_df** (*pandas.DataFrame*) – All IDP pool as classified as per household stock and temperature class

idp_pool_generator()
Description: Create List of Dataframes for each temperature class for each household stock

TYPE list List of dataframes with each element representing a dataframe for every combination of household stock and temperature class

select()
Random assignment of intray-day profiles to each day based on their temeprature class and household stock count

Returns *None.*

temperature_classes()

service_sector

CTS_demand_scale(*aggregation_level*)
Description: caling the demand curves to the annual demand of the respective aggregation level

Parameters **aggregation_level** (*str*) – aggregation_level : str if further processing is to be done in zensus cell level 'other' else 'dsitrict'

Returns

- **CTS_per_district** (*pandas.DataFrame*) –

  if aggregation ='district' Profiles scaled up to annual demand

  else 0

- **CTS_per_grid** (*pandas.DataFrame*) –

  if aggregation ='district' Profiles scaled up to annual demandd

  else 0

- **CTS_per_zensus** (*pandas.DataFrame*) –

  if aggregation ='district' 0

  else Profiles scaled up to annual demand

cts_demand_per_aggregation_level(*aggregation_level*, *scenario*)

Description: Create dataframe assigining the CTS demand curve to individual zensus cell based on their respective NUTS3 CTS curve

Parameters **aggregation_level** (*str*) – if further processing is to be done in zensus cell level 'other' else 'dsitrict'

Returns

- **CTS_per_district** (*pandas.DataFrame*) –

  if aggregation ='district' NUTS3 CTS profiles assigned to individual zensu cells and aggregated per district heat area id

  else empty dataframe

- **CTS_per_grid** (*pandas.DataFrame*) –

  if aggregation ='district' NUTS3 CTS profiles assigned to individual zensu cells and aggregated per mv grid subst id

  else empty dataframe

- **CTS_per_zensus** (*pandas.DataFrame*) –

  if aggregation ='district' empty dataframe

  else NUTS3 CTS profiles assigned to individual zensu population id

class EgonEtragoHeatCts(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

bus_id

p_set

scn_name

class EgonEtragoTimeseriesIndividualHeating(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

bus_id

dist_aggregated_mw

scenario

class EgonIndividualHeatingPeakLoads(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

building_id

scenario

w_th

class EgonTimeseriesDistrictHeating(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

area_id

dist_aggregated_mw

scenario

class HeatTimeSeries(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Chooses heat demand profiles for each residential and CTS building

This dataset creates heat demand profiles in an hourly resoultion. Time series for CTS buildings are created using the SLP-gas method implemented in the demandregio disagregator with the function *export_etrago_cts_heat_profiles()* and stored in the database. Time series for residential buildings are created based on a variety of synthetical created individual demand profiles that are part of *DataBundle*. This method is desribed within the functions and in this publication:

> C. Büttner, J. Amme, J. Endres, A. Malla, B. Schachler, I. Cußmann, Open modeling of electricity and heat demand curves for all residential buildings in Germany, Energy Informatics 5 (1) (2022) 21. doi:10.1186/s42162-022-00201-y.

Dependencies

- *DataBundle*
- *DemandRegio*
- *HeatDemandImport*
- *DistrictHeatingAreas*
- *Vg250*
- *ZensusMvGridDistricts*
- *hh_demand_buildings_setup*
- *WeatherData*

Resulting tables

- *demand.egon_timeseries_district_heating* is created and filled
- *demand.egon_etrago_heat_cts* is created and filled
- *demand.egon_heat_timeseries_selected_profiles* is created and filled
- *demand.egon_daily_heat_demand_per_climate_zone* is created and filled
- *boundaries.egon_map_zensus_climate_zones* is created and filled

name: **str = 'HeatTimeSeries'**

version: **str = '0.0.7'**

calulate_peak_load(*df*, *scenario*)

create_district_heating_profile(*scenario*, *area_id*)

Create heat demand profile for district heating grid including demands of households and service sector.

Parameters

- **scenario** (*str*) – Name of the selected scenario.
- **area_id** (*int*) – Index of the selected district heating grid

Returns **df** (*pandas,DataFrame*) – Hourly heat demand timeseries in MW for the selected district heating grid

create_district_heating_profile_python_like(*scenario='eGon2035'*)

Creates profiles for all district heating grids in one scenario. Similar to create_district_heating_profile but faster and needs more RAM. The results are directly written into the database.

Parameters **scenario** (*str*) – Name of the selected scenario.

Returns *None.*

create_individual_heat_per_mv_grid(*scenario='eGon2035'*, *mv_grid_id=1564*)

create_individual_heating_peak_loads(*scenario='eGon2035'*)

create_individual_heating_profile_python_like(*scenario='eGon2035'*)

create_timeseries_for_building(*building_id*, *scenario*)
Generates final heat demand timeseries for a specific building

Parameters

- **building_id** (*int*) – Index of the selected building
- **scenario** (*str*) – Name of the selected scenario.

Returns *pandas.DataFrame* – Hourly heat demand timeseries in MW for the selected building

district_heating(*method='python'*)

export_etrago_cts_heat_profiles()
Export heat cts load profiles at mv substation level to etrago-table in the database

Returns *None.*

individual_heating_per_mv_grid(*method='python'*)

individual_heating_per_mv_grid_100(*method='python'*)

individual_heating_per_mv_grid_2035(*method='python'*)

individual_heating_per_mv_grid_tables(*method='python'*)

store_national_profiles()

10.5.40 heat_etrago

hts_etrago

The central module creating heat demand time series for the eTraGo tool

class HtsEtragoTable(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Collect heat demand time series for the eTraGo tool

This dataset collects data for individual and district heating demands and writes that into the tables that can be read by the eTraGo tool.

Dependencies

- *DistrictHeatingAreas*
- *HeatEtrago*
- *MvGridDistricts*
- *HeatPumps2035*
- *HeatTimeSeries*

Resulting tables

- *grid.egon_etrago_load* is extended

- *grid.egon_etrago_load_timeseries* is extended

name: str = 'HtsEtragoTable'

version: str = '0.0.6'

hts_to_etrago()

power_to_heat

The central module containing all code dealing with power to heat

assign_electrical_bus(*heat_pumps*, *carrier*, *multiple_per_mv_grid=False*)
Calculates heat pumps per electrical bus

Parameters

- **heat_pumps** (*pandas.DataFrame*) – Heat pumps including voltage level
- **multiple_per_mv_grid** (*boolean, optional*) – Choose if a district heating area can by supplied by multiple hvmv substaions/mv grids. The default is False.

Returns **gdf** (*pandas.DataFrame*) – Heat pumps per electrical bus

assign_voltage_level(*heat_pumps*, *carrier='heat_pump'*)
Assign voltage level to heat pumps

Parameters **heat_pumps** (*pandas.DataFrame*) – Heat pumps without voltage level

Returns **heat_pumps** (*pandas.DataFrame*) – Heat pumps including voltage level

insert_central_power_to_heat(*scenario='eGon2035'*)
Insert power to heat in district heating areas into database

Parameters **scenario** (*str, optional*) – Name of the scenario The default is 'eGon2035'.

Returns *None.*

insert_individual_power_to_heat(*scenario='eGon2035'*)
Insert power to heat into database

Parameters **scenario** (*str, optional*) – Name of the scenario The default is 'eGon2035'.

Returns *None.*

insert_power_to_heat_per_level(*heat_pumps*, *multiple_per_mv_grid*, *carrier='central_heat_pump'*, *scenario='eGon2035'*)
Insert power to heat plants per grid level

Parameters

- **heat_pumps** (*pandas.DataFrame*) – Heat pumps in selected grid level
- **multiple_per_mv_grid** (*boolean*) – Choose if one district heating areas is supplied by one hvmv substation
- **scenario** (*str, optional*) – Name of the scenario The default is 'eGon2035'.

Returns *None.*

The central module containing all code dealing with heat sector in etrago

class HeatEtrago(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Collect data related to the heat sector for the eTraGo tool

This dataset collects data from the heat sector and puts it into a format that is needed for the transmission grid optimisation within the tool eTraGo. It includes the creation of individual and central heat nodes, aggregates the heat supply technologies (apart from CHP) per medium voltage grid district and adds extendable heat stores to each bus. This data is then writing into the corresponding tables that are read by eTraGo.

Dependencies

- *HeatSupply*
- *MvGridDistricts*
- *EtragoSetup*
- *RenewableFeedin*
- *HeatTimeSeries*

Resulting tables

- *grid.egon_etrago_bus* is extended
- *grid.egon_etrago_link* is extended
- *grid.egon_etrago_link_timeseries* is extended
- *grid.egon_etrago_store* is extended
- *grid.egon_etrago_generator* is extended

name: str = 'HeatEtrago'

version: str = '0.0.10'

buses()
Insert individual and district heat buses into eTraGo-tables

Returns *None.*

insert_buses(*carrier*, *scenario*)
Insert heat buses to etrago table

Heat buses are divided into central and individual heating

Parameters

- **carrier** (*str*) – Name of the carrier, either 'central_heat' or 'rural_heat'
- **scenario** (*str, optional*) – Name of the scenario.

insert_central_direct_heat(*scenario='eGon2035'*)
Insert renewable heating technologies (solar and geo thermal)

Parameters **scenario** (*str, optional*) – Name of the scenario The default is 'eGon2035'.

Returns *None.*

insert_central_gas_boilers(*scenario='eGon2035'*)
Inserts gas boilers for district heating to eTraGo-table

Parameters **scenario** (*str, optional*) – Name of the scenario. The default is 'eGon2035'.

Returns *None.*

insert_rural_gas_boilers(*scenario='eGon2035'*)
Inserts gas boilers for individual heating to eTraGo-table

Parameters **scenario** (*str, optional*) – Name of the scenario. The default is 'eGon2035'.

Returns *None.*

insert_store(*scenario*, *carrier*)

store()

supply()
Insert individual and district heat supply into eTraGo-tables

Returns *None.*

10.5.41 heat_supply

district_heating

The central module containing all code dealing with heat supply for district heating areas.

backup_gas_boilers(*scenario*)
Adds backup gas boilers to district heating grids.

Parameters **scenario** (*str*) – Name of the scenario.

Returns *Geopandas.GeoDataFrame* – List of gas boilers for district heating

backup_resistive_heaters(*scenario*)
Adds backup resistive heaters to district heating grids to meet target values of installed capacities.

Parameters **scenario** (*str*) – Name of the scenario.

Returns *Geopandas.GeoDataFrame* – List of gas boilers for district heating

capacity_per_district_heating_category(*district_heating_areas*, *scenario*)
Calculates target values per district heating category and technology

Parameters

- **district_heating_areas** (*geopandas.geodataframe.GeoDataFrame*) – District heating areas per scenario
- **scenario** (*str*) – Name of the scenario

Returns **capacity_per_category** (*pandas.DataFrame*) – Installed capacities per technology and size category

cascade_heat_supply(*scenario*, *plotting=True*)
Assigns supply strategy for ditsrict heating areas.

Different technologies are selected for three categories of district heating areas (small, medium and large annual demand). The technologies are priorized according to Flexibilisierung der Kraft-Wärme-Kopplung; 2017; Forschungsstelle für Energiewirtschaft e.V. (FfE)

Parameters

- **scenario** (*str*) – Name of scenario
- **plotting** (*bool, optional*) – Choose if district heating supply is plotted. The default is True.

Returns **resulting_capacities** (*pandas.DataFrame*) – List of plants per district heating grid

cascade_per_technology(*areas*, *technologies*, *capacity_per_category*, *size_dh*, *max_geothermal_costs=2*)
Add plants of one technology suppliing district heating

Parameters

- **areas** (*geopandas.geodataframe.GeoDataFrame*) – District heating areas which need to be supplied

- **technologies** (*pandas.DataFrame*) – List of supply technologies and their parameters
- **capacity_per_category** (*pandas.DataFrame*) – Target installed capacities per size-category
- **size_dh** (*str*) – Category of the district heating areas
- **max_geothermal_costs** (*float, optional*) – Maxiumal costs of MW geothermal in EUR/MW. The default is 2.

Returns

- **areas** (*geopandas.geodataframe.GeoDataFrame*) – District heating areas which need additional supply technologies
- **technologies** (*pandas.DataFrame*) – List of supply technologies and their parameters
- **append_df** (*pandas.DataFrame*) – List of plants per district heating grid for the selected technology

`plot_heat_supply`(*resulting_capacities*)

`select_district_heating_areas`(*scenario*)

Selects district heating areas per scenario and assigns size-category

Parameters **scenario** (*str*) – Name of the scenario

Returns **district_heating_areas** (*geopandas.geodataframe.GeoDataFrame*) – District heating areas per scenario

`set_technology_data`()

Set data per technology according to Kurzstudie KWK

Returns *pandas.DataFrame* – List of parameters per technology

geothermal

The module containing all code dealing with geothermal potentials and costs

Main source: Ableitung eines Korridors für den Ausbau der erneuerbaren Wärme im Gebäudebereich, Beuth Hochschule für Technik Berlin ifeu – Institut für Energie- und Umweltforschung Heidelberg GmbH Februar 2017

`calc_geothermal_costs`(*max_costs=inf*, *min_costs=0*)

`calc_geothermal_potentials`()

`calc_usable_geothermal_potential`(*max_costs=2*, *min_costs=0*)

Calculate geothermal potentials close to district heating demands

Parameters

- **max_costs** (*float, optional*) – Maximum accepted costs for geo thermal in EUR/MW_th. The default is 2.
- **min_costs** (*float, optional*) – Minimum accepted costs for geo thermal in EUR/MW_th. The default is 0.

Returns *float* – Geothermal potential close to district heating areas in MW

`potential_germany`()

Calculates geothermal potentials for different investment costs.

The investment costs for geothermal district heating highly depend on the location because of different mass flows and drilling depths. Thsi functions calcultaes the geothermal potentials close to germany for five different costs ranges. This data can be used in pypsa-eur-sec to optimise the share of geothermal district heating by considering different investment costs.

Returns *None.*

individual_heating

The central module containing all code dealing with individual heat supply.

The following main things are done in this module:

-
- Desaggregation of heat pump capacities to individual buildings
- Determination of minimum required heat pump capacity for pypsa-eur-sec

The determination of the minimum required heat pump capacity for pypsa-eur-sec takes place in the dataset 'HeatPumpsPypsaEurSec'. The goal is to ensure that the heat pump capacities determined in pypsa-eur-sec are large enough to serve the heat demand of individual buildings after the desaggregation from a few nodes in pypsa-eur-sec to the individual buildings. To determine minimum required heat pump capacity per building the buildings heat peak load in the eGon100RE scenario is used (as pypsa-eur-sec serves as the scenario generator for the eGon100RE scenario; see *determine_minimum_hp_capacity_per_building()* for information on how minimum required heat pump capacity is determined). As the heat peak load is not previously determined, it is as well done in the course of this task. Further, as determining heat peak load requires heat load profiles of the buildings to be set up, this task is also utilised to set up heat load profiles of all buildings with heat pumps within a grid in the eGon100RE scenario used in eTraGo. The resulting data is stored in separate tables respectively a csv file:

- ***input-pypsa-eur-sec/minimum_hp_capacity_mv_grid_100RE.csv*:** This csv file contains minimum required heat pump capacity per MV grid in MW as input for pypsa-eur-sec. It is created within *export_min_cap_to_csv()*.
- ***demand.egon_etrago_timeseries_individual_heating*:** This table contains aggregated heat load profiles of all buildings with heat pumps within an MV grid in the eGon100RE scenario used in eTraGo. It is created within `individual_heating_per_mv_grid_tables()`.
- ***demand.egon_building_heat_peak_loads*:** Mapping of peak heat demand and buildings including cell_id, building, area and peak load. This table is created in *delete_heat_peak_loads_100RE()*.

The desaggregation of heat pump capcacities to individual buildings takes place in two separate datasets: 'HeatPumps2035' for eGon2035 scenario and 'HeatPumps2050' for eGon100RE. It is done separately because for one reason in case of the eGon100RE scenario the minimum required heat pump capacity per building can directly be determined using the heat peak load per building determined in the dataset 'HeatPumpsPypsaEurSec', whereas heat peak load data does not yet exist for the eGon2035 scenario. Another reason is, that in case of the eGon100RE scenario all buildings with individual heating have a heat pump whereas in the eGon2035 scenario buildings are randomly selected until the installed heat pump capacity per MV grid is met. All other buildings with individual heating but no heat pump are assigned a gas boiler.

In the 'HeatPumps2035' dataset the following things are done. First, the building's heat peak load in the eGon2035 scenario is determined for sizing the heat pumps. To this end, heat load profiles per building are set up. Using the heat peak load per building the minimum required heat pump capacity per building is determined (see *determine_minimum_hp_capacity_per_building()*). Afterwards, the total heat pump capacity per MV grid is desaggregated to individual buildings in the MV grid, wherefore buildings are randomly chosen until the MV grid's total heat pump capacity is reached (see *determine_buildings_with_hp_in_mv_grid()*). Buildings with PV rooftop plants are more likely to be assigned a heat pump. In case the minimum heat pump capacity of all chosen buildings is smaller than the total heat pump capacity of the MV grid but adding another building would exceed the total heat pump capacity of the MV grid, the remaining capacity is distributed to all buildings with heat pumps proportionally to the size of their respective minimum heat pump capacity. Therefore, the heat pump capacity of a building can be larger than the minimum required heat pump capacity. The generated heat load profiles per building are in a last step utilised to set up heat load profiles of all buildings with heat pumps within a grid as well as for all buildings with a

gas boiler (i.e. all buildings with decentral heating system minus buildings with heat pump) needed in eTraGo. The resulting data is stored in the following tables:

- ***demand.egon_hp_capacity_buildings*:** This table contains the heat pump capacity of all buildings with a heat pump. It is created within *delete_hp_capacity_2035()*.
- ***demand.egon_etrago_timeseries_individual_heating*:** This table contains aggregated heat load profiles of all buildings with heat pumps within an MV grid as well as of all buildings with gas boilers within an MV grid in the eGon100RE scenario used in eTraGo. It is created within `individual_heating_per_mv_grid_tables()`.
- ***demand.egon_building_heat_peak_loads*:** Mapping of heat demand time series and buildings including cell_id, building, area and peak load. This table is created in *delete_heat_peak_loads_2035()*.

In the 'HeatPumps2050' dataset the total heat pump capacity in each MV grid can be directly desaggregated to individual buildings, as the building's heat peak load was already determined in the 'HeatPumpsPypsaEurSec' dataset. Also in contrast to the 'HeatPumps2035' dataset, all buildings with decentral heating system are assigned a heat pump, wherefore no random sampling of buildings needs to be conducted. The resulting data is stored in the following table:

- ***demand.egon_hp_capacity_buildings*:** This table contains the heat pump capacity of all buildings with a heat pump. It is created within *delete_hp_capacity_2035()*.

The following datasets from the database are mainly used for creation:

- *boundaries.egon_map_zensus_grid_districts*:
- *boundaries.egon_map_zensus_district_heating_areas*:
- ***demand.egon_peta_heat*:** Table of annual heat load demand for residential and cts at census cell level from peta5.
- *demand.egon_heat_timeseries_selected_profiles*:
- *demand.egon_heat_idp_pool*:
- *demand.egon_daily_heat_demand_per_climate_zone*:
- ***boundaries.egon_map_zensus_mvgd_buildings*:** A final mapping table including all buildings used for residential and cts, heat and electricity timeseries. Including census cells, mvgd bus_id, building type (osm or synthetic)
- *supply.egon_individual_heating*:
- ***demand.egon_cts_heat_demand_building_share*:** Table including the mv substation heat profile share of all selected cts buildings for scenario eGon2035 and eGon100RE. This table is created within `cts_heat()`

What is the goal?

The goal is threefold. Primarily, heat pump capacity of individual buildings is determined as it is necessary for distribution grid analysis. Secondly, as heat demand profiles need to be set up during the process, the heat demand profiles of all buildings with individual heat pumps respectively gas boilers per MV grid are set up to be used in eTraGo. Thirdly, minimum heat pump capacity is determined as input for pypsa-eur-sec to avoid that heat pump capacity per building is too little to meet the heat demand after desaggregation to individual buildings.

What is the challenge?

The main challenge lies in the set up of heat demand profiles per building in *aggregate_residential_and_cts_profiles()* as it takes alot of time and in grids with a high number of buildings requires alot of RAM. Both runtime and RAM usage needed to be improved several times. To speed up the process, tasks are set up to run in parallel. This currently leads to alot of connections being opened and at a certain point to a runtime error due to too many open connections.

What are central assumptions during the data processing?

Central assumption for determining minimum heat pump capacity and desaggregating heat pump capacity to individual buildings is that the required heat pump capacity is determined using an approach from the network development plan (pp.46-47) (see *determine_minimum_hp_capacity_per_building()*). There, the heat pump capacity is determined by multiplying the heat peak demand of the building by a minimum assumed COP of 1.7 and a flexibility factor of 24/18, taking into account that power supply of heat pumps can be interrupted for up to six hours by the local distribution grid operator. Another central assumption is, that buildings with PV rooftop plants are more likely to have a heat pump than other buildings (see *determine_buildings_with_hp_in_mv_grid()* for details)

Drawbacks and limitations of the data

In the eGon2035 scenario buildings with heat pumps are selected randomly with a higher probability for a heat pump for buildings with PV rooftop (see *determine_buildings_with_hp_in_mv_grid()* for details). Another limitation may be the sizing of the heat pumps, as in the eGon2035 scenario their size rigidly depends on the heat peak load and a fixed flexibility factor. During the coldest days of the year, heat pump flexibility strongly depends on this assumption and cannot be dynamically enlarged to provide more flexibility (or only slightly through larger heat storage units).

Notes

This module docstring is rather a dataset documentation. Once, a decision is made in … the content of this module docstring needs to be moved to docs attribute of the respective dataset class.

class BuildingHeatPeakLoads(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

building_id

peak_load_in_w

scenario

sector

class EgonEtragoTimeseriesIndividualHeating(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

bus_id

carrier

dist_aggregated_mw

scenario

class EgonHpCapacityBuildings(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

building_id

hp_capacity

scenario

class HeatPumps2035(*dependencies*)

Bases: *egon.data.datasets.Dataset*

name: str

The name of the Dataset

version: str

The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

class HeatPumps2050(*dependencies*)
Bases: egon.data.datasets.Dataset

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

class HeatPumpsPypsaEurSec(*dependencies*)
Bases: egon.data.datasets.Dataset

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

adapt_numpy_float64(*numpy_float64*)

adapt_numpy_int64(*numpy_int64*)

aggregate_residential_and_cts_profiles(*mvgd*, *scenario*)
Gets residential and CTS heat demand profiles per building and aggregates them.

Parameters

- **mvgd** (*int*) – MV grid ID.
- **scenario** (*str*) – Possible options are eGon2035 or eGon100RE.

Returns *pd.DataFrame* – Table of demand profile per building. Column names are building IDs and index is hour of the year as int (0-8759).

calc_residential_heat_profiles_per_mvgd(*mvgd*, *scenario*)
Gets residential heat profiles per building in MV grid for either eGon2035 or eGon100RE scenario.

Parameters

- **mvgd** (*int*) – MV grid ID.
- **scenario** (*str*) – Possible options are eGon2035 or eGon100RE.

Returns

pd.DataFrame –

Heat demand profiles of buildings. Columns are:

- **zensus_population_id** [int] Zensus cell ID building is in.
- **building_id** [int] ID of building.
- **day_of_year** [int] Day of the year (1 - 365).
- **hour** [int] Hour of the day (1 - 24).
- **demand_ts** [float] Building's residential heat demand in MW, for specified hour of the year (specified through columns *day_of_year* and *hour*).

cascade_heat_supply_indiv(*scenario*, *distribution_level*, *plotting=True*)
Assigns supply strategy for individual heating in four steps.

1.) all small scale CHP are connected. 2.) If the supply can not meet the heat demand, solar thermal collectors

are attached. This is not implemented yet, since individual solar thermal plants are not considered in eGon2035 scenario.

3.) If this is not suitable, the mv grid is also supplied by heat pumps. 4.) The last option are individual gas boilers.

Parameters

- **scenario** (*str*) – Name of scenario
- **plotting** (*bool, optional*) – Choose if individual heating supply is plotted. The default is True.

Returns **resulting_capacities** (*pandas.DataFrame*) – List of plants per mv grid

cascade_per_technology(*heat_per_mv*, *technologies*, *scenario*, *distribution_level*, *max_size_individual_chp=0.05*)
Add plants for individual heat. Currently only on mv grid district level.

Parameters

- **mv_grid_districts** (*geopandas.geodataframe.GeoDataFrame*) – MV grid districts including the heat demand
- **technologies** (*pandas.DataFrame*) – List of supply technologies and their parameters
- **scenario** (*str*) – Name of the scenario
- **max_size_individual_chp** (*float*) – Maximum capacity of an individual chp in MW

Returns

- **mv_grid_districts** (*geopandas.geodataframe.GeoDataFrame*) – MV grid district which need additional individual heat supply
- **technologies** (*pandas.DataFrame*) – List of supply technologies and their parameters
- **append_df** (*pandas.DataFrame*) – List of plants per mv grid for the selected technology

catch_missing_buidings(*buildings_decentral_heating*, *peak_load*)
Check for missing buildings and reduce the list of buildings with decentral heating if no peak loads available. This should only happen in case of cutout SH

Parameters

- **buildings_decentral_heating** (*list(int)*) – Array or list of buildings with decentral heating
- **peak_load** (*pd.Series*) – Peak loads of all building within the mvgd

delete_heat_peak_loads_100RE()
Remove all heat peak loads for eGon100RE.

delete_heat_peak_loads_2035()
Remove all heat peak loads for eGon2035.

delete_hp_capacity(*scenario*)
Remove all hp capacities for the selected scenario

Parameters **scenario** (*string*) – Either eGon2035 or eGon100RE

delete_hp_capacity_100RE()
Remove all hp capacities for the selected eGon100RE

delete_hp_capacity_2035()
Remove all hp capacities for the selected eGon2035

delete_mvgd_ts(*scenario*)
Remove all hp capacities for the selected scenario

Parameters **scenario** (*string*) – Either eGon2035 or eGon100RE

delete_mvgd_ts_100RE()
Remove all mvgd ts for the selected eGon100RE

delete_mvgd_ts_2035()
Remove all mvgd ts for the selected eGon2035

delete_pypsa_eur_sec_csv_file()
Delete pypsa eur sec minimum heat pump capacity csv before new run

desaggregate_hp_capacity(*min_hp_cap_per_building*, *hp_cap_mv_grid*)
Desaggregates the required total heat pump capacity to buildings.

All buildings are previously assigned a minimum required heat pump capacity. If the total heat pump capacity exceeds this, larger heat pumps are assigned.

Parameters

- **min_hp_cap_per_building** (*pd.Series*) –

  Pandas series with minimum required heat pump capacity per building in MW.

- **hp_cap_mv_grid** (*float*) – Total heat pump capacity in MW in given MV grid.

Returns *pd.Series* – Pandas series with heat pump capacity per building in MW.

determine_buildings_with_hp_in_mv_grid(*hp_cap_mv_grid*, *min_hp_cap_per_building*)
Distributes given total heat pump capacity to buildings based on their peak heat demand.

Parameters

- **hp_cap_mv_grid** (*float*) – Total heat pump capacity in MW in given MV grid.
- **min_hp_cap_per_building** (*pd.Series*) –

  Pandas series with minimum required heat pump capacity per building in MW.

Returns *pd.Index(int)* – Building IDs (as int) of buildings to get heat demand time series for.

determine_hp_cap_buildings_eGon100RE()
Main function to determine HP capacity per building in eGon100RE scenario.

determine_hp_cap_buildings_eGon100RE_per_mvgd(*mv_grid_id*)
Determines HP capacity per building in eGon100RE scenario.

In eGon100RE scenario all buildings without district heating get a heat pump.

Returns *pd.Series* – Pandas series with heat pump capacity per building in MW.

determine_hp_cap_buildings_eGon2035_per_mvgd(*mv_grid_id*, *peak_heat_demand*, *building_ids*)
Determines which buildings in the MV grid will have a HP (buildings with PV rooftop are more likely to be assigned) in the eGon2035 scenario, as well as their respective HP capacity in MW.

Parameters

- **mv_grid_id** (*int*) – ID of MV grid.
- **peak_heat_demand** (*pd.Series*) – Series with peak heat demand per building in MW. Index contains the building ID.

- **building_ids** (*pd.Index(int)*) – Building IDs (as int) of buildings with decentral heating system in given MV grid.

determine_hp_cap_peak_load_mvgd_ts_2035(*mvgd_ids*)
Main function to determine HP capacity per building in eGon2035 scenario. Further, creates heat demand time series for all buildings with heat pumps in MV grid, as well as for all buildings with gas boilers, used in eTraGo.

Parameters **mvgd_ids** (*list(int)*) – List of MV grid IDs to determine data for.

determine_hp_cap_peak_load_mvgd_ts_pypsa_eur_sec(*mvgd_ids*)
Main function to determine minimum required HP capacity in MV for pypsa-eur-sec. Further, creates heat demand time series for all buildings with heat pumps in MV grid in eGon100RE scenario, used in eTraGo.

Parameters **mvgd_ids** (*list(int)*) – List of MV grid IDs to determine data for.

determine_min_hp_cap_buildings_pypsa_eur_sec(*peak_heat_demand*, *building_ids*)
Determines minimum required HP capacity in MV grid in MW as input for pypsa-eur-sec.

Parameters

- **peak_heat_demand** (*pd.Series*) – Series with peak heat demand per building in MW. Index contains the building ID.
- **building_ids** (*pd.Index(int)*) – Building IDs (as int) of buildings with decentral heating system in given MV grid.

Returns *float* – Minimum required HP capacity in MV grid in MW.

determine_minimum_hp_capacity_per_building(*peak_heat_demand*, *flexibility_factor=1.3333333333333333*, *cop=1.7*)
Determines minimum required heat pump capacity.

Parameters

- **peak_heat_demand** (*pd.Series*) – Series with peak heat demand per building in MW. Index contains the building ID.
- **flexibility_factor** (*float*) – Factor to overdimension the heat pump to allow for some flexible dispatch in times of high heat demand. Per default, a factor of 24/18 is used, to take into account

Returns *pd.Series* – Pandas series with minimum required heat pump capacity per building in MW.

export_min_cap_to_csv(*df_hp_min_cap_mv_grid_pypsa_eur_sec*)
Export minimum capacity of heat pumps for pypsa eur sec to csv

export_to_db(*df_peak_loads_db*, *df_heat_mvgd_ts_db*, *drop=False*)
Function to export the collected results of all MVGDs per bulk to DB.

Parameters

df_peak_loads_db [pd.DataFrame] Table of building peak loads of all MVGDs per bulk

df_heat_mvgd_ts_db [pd.DataFrame] Table of all aggregated MVGD profiles per bulk

drop [boolean] Drop and recreate table if True

get_buildings_with_decentral_heat_demand_in_mv_grid(*mvgd*, *scenario*)
Returns building IDs of buildings with decentral heat demand in given MV grid.

As cells with district heating differ between scenarios, this is also depending on the scenario. CTS and residential have to be retrieved seperatly as some residential buildings only have electricity but no heat demand. This does not occure in CTS.

Parameters

- **mvgd** (*int*) – ID of MV grid.
- **scenario** (*str*) – Name of scenario. Can be either "eGon2035" or "eGon100RE".

Returns *pd.Index(int)* – Building IDs (as int) of buildings with decentral heating system in given MV grid. Type is pandas Index to avoid errors later on when it is used in a query.

`get_cts_buildings_with_decentral_heat_demand_in_mv_grid`(*scenario*, *mv_grid_id*)
Returns building IDs of buildings with decentral CTS heat demand in given MV grid.

As cells with district heating differ between scenarios, this is also depending on the scenario.

Parameters

- **scenario** (*str*) – Name of scenario. Can be either "eGon2035" or "eGon100RE".
- **mv_grid_id** (*int*) – ID of MV grid.

Returns *pd.Index(int)* – Building IDs (as int) of buildings with decentral heating system in given MV grid. Type is pandas Index to avoid errors later on when it is used in a query.

`get_daily_demand_share`(*mvgd*)
per census cell :Parameters: **mvgd** (*int*) – MVGD id

Returns **df_daily_demand_share** (*pd.DataFrame*) – Daily annual demand share per cencus cell. Columns of the dataframe are zensus_population_id, day_of_year and daily_demand_share.

`get_daily_profiles`(*profile_ids*)

Parameters **profile_ids** (*list(int)*) – daily heat profile ID's

Returns **df_profiles** (*pd.DataFrame*) – Residential daily heat profiles. Columns of the dataframe are idp, house, temperature_class and hour.

`get_heat_peak_demand_per_building`(*scenario*, *building_ids*)

`get_peta_demand`(*mvgd*, *scenario*)
Retrieve annual peta heat demand for residential buildings for either eGon2035 or eGon100RE scenario.

Parameters

- **mvgd** (*int*) – MV grid ID.
- **scenario** (*str*) – Possible options are eGon2035 or eGon100RE

Returns **df_peta_demand** (*pd.DataFrame*) – Annual residential heat demand per building and scenario. Columns of the dataframe are zensus_population_id and demand.

`get_residential_buildings_with_decentral_heat_demand_in_mv_grid`(*scenario*, *mv_grid_id*)
Returns building IDs of buildings with decentral residential heat demand in given MV grid.

As cells with district heating differ between scenarios, this is also depending on the scenario.

Parameters

- **scenario** (*str*) – Name of scenario. Can be either "eGon2035" or "eGon100RE".
- **mv_grid_id** (*int*) – ID of MV grid.

Returns *pd.Index(int)* – Building IDs (as int) of buildings with decentral heating system in given MV grid. Type is pandas Index to avoid errors later on when it is used in a query.

`get_residential_heat_profile_ids`(*mvgd*)
Retrieve 365 daily heat profiles ids per residential building and selected mvgd.

Parameters **mvgd** (*int*) – ID of MVGD

Returns **df_profiles_ids** (*pd.DataFrame*) – Residential daily heat profile ID's per building. Columns of the dataframe are zensus_population_id, building_id, selected_idp_profiles, buildings and day_of_year.

get_total_heat_pump_capacity_of_mv_grid(*scenario*, *mv_grid_id*)

Returns total heat pump capacity per grid that was previously defined (by NEP or pypsa-eur-sec).

Parameters

- **scenario** (*str*) – Name of scenario. Can be either "eGon2035" or "eGon100RE".
- **mv_grid_id** (*int*) – ID of MV grid.

Returns *float* – Total heat pump capacity in MW in given MV grid.

get_zensus_cells_with_decentral_heat_demand_in_mv_grid(*scenario*, *mv_grid_id*)

Returns zensus cell IDs with decentral heating systems in given MV grid.

As cells with district heating differ between scenarios, this is also depending on the scenario.

Parameters

- **scenario** (*str*) – Name of scenario. Can be either "eGon2035" or "eGon100RE".
- **mv_grid_id** (*int*) – ID of MV grid.

Returns *pd.Index(int)* – Zensus cell IDs (as int) of buildings with decentral heating systems in given MV grid. Type is pandas Index to avoid errors later on when it is used in a query.

plot_heat_supply(*resulting_capacities*)

split_mvgds_into_bulks(*n*, *max_n*, *func*)

Generic function to split task into multiple parallel tasks, dividing the number of MVGDs into even bulks.

Parameters

- **n** (*int*) – Number of bulk
- **max_n** (*int*) – Maximum number of bulks
- **func** (*function*) – The funnction which is then called with the list of MVGD as parameter.

The central module containing all code dealing with heat supply data

class EgonDistrictHeatingSupply(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

capacity

carrier

category

district_heating_id

geometry

index

scenario

class EgonIndividualHeatingSupply(***kwargs*)

Bases: `sqlalchemy.ext.declarative.api.Base`

capacity

carrier

category

geometry

index

mv_grid_id

scenario

class HeatSupply(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Select and store heat supply technologies for inidvidual and district heating

This dataset distributes heat supply technologies to each district heating grid and individual supplies buildings per medium voltage grid district. National installed capacities are predefined from external sources within *ScenarioCapacities*. The further distribution is done using a cascade that follows a specific order of supply technologies and the heat demand.

Dependencies

- *DataBundle*
- *DistrictHeatingAreas*
- *ZensusMvGridDistricts*
- *Chp*

Resulting tables

- *demand.egon_district_heating* is created and filled
- *demand.egon_individual_heating* is created and filled

name: str = 'HeatSupply'

version: str = '0.0.8'

create_tables()

Create tables for district heating areas

Returns *None*

district_heating()

Insert supply for district heating areas

Returns *None.*

individual_heating()

Insert supply for individual heating

Returns *None.*

10.5.42 hydrogen_etrago

bus

The central module containing all code dealing with the hydrogen buses

In this module, the functions allowing to create the H2 buses in Germany for eTraGo are to be found. The H2 buses in the neighbouring countries (only present in eGon100RE) are defined in *pypsaeursec*. In both scenarios, there are two types of H2 buses in Germany:

- H2_grid buses: defined in *insert_H2_buses_from_CH4_grid()*; these buses are located at the places of the CH4 buses.
- H2_saltcavern buses: defined in *insert_H2_buses_from_saltcavern()*; these buses are located at the intersection of AC buses and potential H2 saltcaverns.

insert_H2_buses_from_CH4_grid(*gdf*, *carrier*, *target*, *scn_name*)
Insert the H2 buses based on CH4 grid into the database.

At each CH4 location, respectively at each intersection of the CH4 grid, a H2 bus is created.

Parameters

- **gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing the empty bus data.
- **carrier** (*str*) – Name of the carrier.
- **target** (*dict*) – Target schema and table information.
- **scn_name** (*str*) – Name of the scenario.

Returns *None*

insert_H2_buses_from_saltcavern(*gdf*, *carrier*, *sources*, *target*, *scn_name*)
Insert the H2 buses based on saltcavern locations into the database.

These buses are located at the intersection of AC buses and potential H2 saltcaverns.

Parameters

- **gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing the empty bus data.
- **carrier** (*str*) – Name of the carrier.
- **sources** (*dict*) – Sources schema and table information.
- **target** (*dict*) – Target schema and table information.
- **scn_name** (*str*) – Name of the scenario.

Returns *None*

insert_hydrogen_buses(*scenario='eGon2035'*)
Insert hydrogen buses into the database (in etrago table)

Hydrogen buses are inserted into the database using the functions:

- *insert_H2_buses_from_CH4_grid()* for H2_grid buses
- *insert_H2_buses_from_saltcavern()* for the H2_saltcavern buses

Parameters **scenario** (*str, optional*) – Name of the scenario, the default is 'eGon2035'.

Returns *None*

insert_hydrogen_buses_eGon100RE()
Copy H2 buses from the eGon2035 to the eGon100RE scenario.

Returns *None*

h2_grid

The central module containing all code dealing with the H2 grid in eGon100RE

The H2 grid, present only in eGon100RE, is composed of two parts:

- a fixed part with the same topology as the CH4 grid and with carrier 'H2_retrofit' corresponding to the retrofitted share of the CH4 grid into a hydrogen grid,
- an extendable part with carrier 'H2_gridextension', linking each H2_salcavern bus to the closest H2_grid bus: this part has no capacity (p_nom = 0) but it can be extended.

As for the CH4 grid, the H2 pipelines are modelled by PyPSA links.

insert_h2_pipelines()
Insert hydrogen grid (H2 links) into the database for eGon100RE.

Insert the H2 grid by executing the following steps:

- Copy the CH4 links in Germany from eGon2035
- **Overwrite the followings columns:**
  - bus0 and bus1 using the grid.egon_etrago_ch4_h2 table
  - carrier, scn_name
  - p_nom: the value attributed there corresponds to the share of p_nom of the specific pipeline that could be retrofited into H2 pipeline. This share is the same for every pipeline and is calculated in the PyPSA-eur-sec run.
- Create new extendable pipelines to link the existing grid to the H2_saltcavern buses
- Clean database
- Attribute link_id to the links
- Insert into the database

Returns *None*

h2_to_ch4

Module containing the definition of the links between H2 and CH4 buses

In this module the functions used to define and insert the links between H2 and CH4 buses into the database are to be found. These links are modelling:

- Methanisation (carrier name: 'H2_to_CH4'): technology to produce CH4 from H2
- H2_feedin: Injection of H2 into the CH4 grid
- Steam Methane Reaction (SMR, carrier name: 'CH4_to_H2'): techonology to produce CH4 from H2

H2_CH4_mix_energy_fractions(*x*, *T=25*, *p=50*)
Calculate the fraction of H2 with respect to energy in a H2 CH4 mixture.

Given the volumetric fraction of H2 in a H2 and CH4 mixture, the fraction of H2 with respect to energy is calculated with the ideal gas mixture law. Beware, that changing the fraction of H2 changes the overall energy

within a specific volume of the mixture. If H2 is fed into CH4, the pipeline capacity (based on energy) therefore decreases if the volumetric flow does not change. This effect is neglected in eGon. At 15 vol% H2 the decrease in capacity equals about 10 % if volumetric flow does not change.

Parameters

- **x** (*float*) – Volumetric fraction of H2 in the mixture
- **T** (*int, optional*) – Temperature of the mixture in °C, by default 25
- **p** (*int, optional*) – Pressure of the mixture in bar, by default 50

Returns *float* – Fraction of H2 in mixture with respect to energy (LHV)

insert_h2_to_ch4_eGon100RE()
Copy H2/CH4 links from the eGon2035 to the eGon100RE scenario.

insert_h2_to_ch4_to_h2()
Inserts methanisation, feedin and SMR links into the database

Define the potentials for methanisation and Steam Methane Reaction (SMR) modelled as extendable links as well as the H2 feedin capacities modelled as non extendable links and insert all of them into the database. These tree technologies are connecting CH4 and H2_grid buses only.

The capacity of the H2_feedin links is considerated as constant and calculated as the sum of the capacities of the CH4 links connected to the CH4 bus multiplied by the H2 energy share allowed to be fed in. This share is calculated in the function *H2_CH4_mix_energy_fractions()*.

Returns *None*

power_to_h2

Module containing the definition of the AC grid to H2 links

In this module the functions used to define and insert the links between H2 and AC buses into the database are to be found. These links are modelling:

- Electrolysis (carrier name: 'power_to_H2'): technology to produce H2 from AC
- Fuel cells (carrier name: 'H2_to_power'): techonology to produce power from H2

insert_power_to_h2_to_power(*scn_name='eGon2035'*)
Insert electrolysis and fuel cells capacities into the database.

The potentials for power-to-H2 in electrolysis and H2-to-power in fuel cells are created between each H2 bus (H2_grid and H2_saltcavern) and its closest HV power bus. These links are extendable. For the electrolysis, if the distance between the AC and the H2 bus is > 500m, the maximum capacity of the installation is limited to 1 MW.

Parameters **scn_name** (*str*) – Name of the scenario

Returns *None*

insert_power_to_h2_to_power_eGon100RE()
Copy H2/power links from the eGon2035 to the eGon100RE scenario.

Returns *None*

map_buses(*scn_name*)
Map H2 buses to nearest HV AC bus.

Parameters **scn_name** (*str*) – Name of the scenario.

Returns **gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame with connected buses.

storage

The central module containing all code dealing with H2 stores in Germany

This module contains the functions used to insert the two types of H2 store potentials in Germany:

- H2 overground stores (carrier: 'H2_overground'): steel tanks at every H2_grid bus
- H2 underground stores (carrier: 'H2_underground'): saltcavern store at every H2_saltcavern bus. NB: the saltcavern locations define the H2_saltcavern buses locations.

All these stores are modelled as extendable PyPSA stores.

calculate_and_map_saltcavern_storage_potential()
Calculate site specific storage potential based on InSpEE-DS report.

Returns *None*

insert_H2_overground_storage(*scn_name='eGon2035'*)
Insert H2_overground stores into the database.

Insert extendable H2_overground stores (steel tanks) at each H2_grid bus.

Returns *None*

insert_H2_saltcavern_storage(*scn_name='eGon2035'*)
Insert H2_underground stores into the database.

Insert extendable H2_underground stores (saltcavern potentials) at every H2_saltcavern bus.

Returns *None*

insert_H2_storage_eGon100RE()
Copy H2 storage from the eGon2035 to the eGon100RE scenario.

Returns *None*

write_saltcavern_potential()
Write saltcavern potentials into the database

Returns *None*

The central module containing the definitions of the datasets linked to H2

This module contains the definitions of the datasets linked to the hydrogen sector in eTraGo in Germany.

In the eGon2035 scenario, there is no H2 bus abroad, so technologies linked to the hydrogen sector are present only in Germany.

In the eGon100RE scenario, the potential and installed capacities abroad arrise from the PyPSA-eur-sec run. For this reason, this module focuses only on the hydrogen related components in Germany, and the module *pypsaeursec* on the hydrogen related components abroad.

class HydrogenBusEtrago(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Insert the H2 buses into the database for Germany

Insert the H2 buses in Germany into the database for the scenarios eGon2035 and eGon100RE by executing successively the functions *calculate_and_map_saltcavern_storage_potential*, *insert_hydrogen_buses* and *insert_hydrogen_buses_eGon100RE*.

Dependencies

- *SaltcavernData*
- *GasNodesAndPipes*

- *SubstationVoronoi*

Resulting

- *grid.egon_etrago_bus* is extended

name: str = 'HydrogenBusEtrago'

version: str = '0.0.1'

class HydrogenGridEtrago(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Insert the H2 grid in Germany into the database for eGon100RE

Insert the H2 links (pipelines) into Germany in the database for the scenario eGon100RE by executing the function *insert_h2_pipelines*.

Dependencies

- *SaltcavernData*
- *GasNodesAndPipes*
- *SubstationVoronoi*
- *GasAreaseGon2035*
- *PypsaEurSec*
- *HydrogenBusEtrago*

Resulting

- *grid.egon_etrago_link* is extended

name: str = 'HydrogenGridEtrago'

version: str = '0.0.2'

class HydrogenMethaneLinkEtrago(*dependencies*)

Bases: *egon.data.datasets.Dataset*

Insert the methanisation, feed in and SMR into the database

Insert the the methanisation, feed in (only in eGon2035) and Steam Methane Reaction (SMR) links in Germany into the database for the scenarios eGon2035 and eGon100RE by executing successively the functions *insert_h2_to_ch4_to_h2* and *insert_h2_to_ch4_eGon100RE*.

Dependencies

- *SaltcavernData*
- *GasNodesAndPipes*
- *SubstationVoronoi*
- *HydrogenBusEtrago*
- *HydrogenGridEtrago*
- *HydrogenPowerLinkEtrago*

Resulting

- *grid.egon_etrago_link* is extended

name: str = 'HydrogenMethaneLinkEtrago'

version: str = '0.0.5'

class HydrogenPowerLinkEtrago(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Insert the electrolysis and the fuel cells into the database

Insert the the electrolysis and the fuel cell links in Germany into the database for the scenarios eGon2035 and eGon100RE by executing successively the functions *insert_power_to_h2_to_power* and *insert_power_to_h2_to_power_eGon100RE*.

Dependencies

- *SaltcavernData*
- *GasNodesAndPipes*
- *SubstationVoronoi*
- *HydrogenBusEtrago*
- *HydrogenGridEtrago*

Resulting

- *grid.egon_etrago_link* is extended

name: str = 'HydrogenPowerLinkEtrago'

version: str = '0.0.4'

class HydrogenStoreEtrago(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Insert the H2 stores into the database for Germany

Insert the H2 stores in Germany into the database for the scenarios eGon2035 and eGon100RE:

- H2 overground stores or steel tanks at each H2_grid bus with the function *insert_H2_overground_storage* for the scenario eGon2035,
- H2 underground stores or saltcavern stores at each H2_saltcavern bus with the function *insert_H2_saltcavern_storage* for the scenario eGon2035,
- H2 stores (overground and underground) for the scenario eGon100RE with the function *insert_H2_storage_eGon100RE*.

Dependencies

- *SaltcavernData*
- *GasNodesAndPipes*
- *SubstationVoronoi*
- *HydrogenBusEtrago*
- *HydrogenGridEtrago*
- *GasNodesAndPipes*

Resulting

- *grid.egon_etrago_store* is extended

name: str = 'HydrogenStoreEtrago'

version: str = '0.0.3'

10.5.43 industrial_sites

The central module containing all code dealing with the spatial distribution of industrial electricity demands. Industrial demands from DemandRegio are distributed from nuts3 level down to osm landuse polygons and/or industrial sites also identified within this processing step bringing three different inputs together.

class HotmapsIndustrialSites(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

address

city

citycode

companyname

country

datasource

emissions_eprtr_2014

emissions_ets_2014

excess_heat_100_200C

excess_heat_200_500C

excess_heat_500C

excess_heat_total

fuel_demand

geom

location

production

siteid

sitename

subsector

wz

class IndustrialSites(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

address

companyname

geom

id

nuts3

subsector

wz

class MergeIndustrialSites(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

class SchmidtIndustrialSites(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

annual_tonnes

application

capacity_production

geom

id

landkreis_number

lat

lon

plant

wz

class SeenergiesIndustrialSites(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

address

companyname

country

electricitydemand_tj

eu28

excess_heat

fueldemand_tj

geom

globalid

lat

level_1_pj

level_1_r_pj

level_1_r_tj

level_1_tj

level_2_pj

level_2_r_pj

level_2_r_tj

level_2_tj

level_3_pj

level_3_r_pj

level_3_r_tj

level_3_tj

lon

nuts1

nuts3

objectid

siteid

subsector

wz

create_tables()
Create tables for industrial sites and distributed industrial demands :returns: *None.*

download_hotmaps()
Download csv file on hotmap's industrial sites.

download_import_industrial_sites()
Wraps different functions to create tables, download csv files containing information on industrial sites in Germany and write this data to the local postgresql database

Returns *None.*

download_seenergies()
Download csv file on s-eenergies' industrial sites.

hotmaps_to_postgres()
Import hotmaps data to postgres database

map_nuts3()
Match resulting industrial sites with nuts3 codes and fill column 'nuts3'

Returns *None.*

merge_inputs()
Merge and clean data from different sources (hotmaps, seenergies, Thesis Schmidt)

schmidt_to_postgres()
Import data from Thesis by Danielle Schmidt to postgres database

seenergies_to_postgres()
Import seenergies data to postgres database

10.5.44 industry

temporal

The central module containing all code dealing with processing timeseries data using demandregio

`calc_load_curves_ind_osm`(*scenario*)
Temporal disaggregate electrical demand per osm industrial landuse area.

Parameters **scenario** (*str*) – Scenario name.

Returns *pandas.DataFrame* – Demand timeseries of industry allocated to osm landuse areas and aggregated per substation id

`calc_load_curves_ind_sites`(*scenario*)
Temporal disaggregation of load curves per industrial site and industrial subsector.

Parameters **scenario** (*str*) – Scenario name.

Returns *pandas.DataFrame* – Demand timeseries of industry allocated to industrial sites and aggregated per substation id and industrial subsector

`identify_bus`(*load_curves*, *demand_area*)
Identify the grid connection point for a consumer by determining its grid level based on the time series' peak load and the spatial intersection to mv grid districts or ehv voronoi cells.

Parameters

- **load_curves** (*pandas.DataFrame*) – Demand timeseries per demand area (e.g. osm landuse area, industrial site)
- **demand_area** (*pandas.DataFrame*) – Dataframe with id and geometry of areas where an industrial demand is assigned to, such as osm landuse areas or industrial sites.

Returns *pandas.DataFrame* – Aggregated industrial demand timeseries per bus

`identify_voltage_level`(*df*)
Identify the voltage_level of a grid component based on its peak load and defined thresholds.

Parameters **df** (*pandas.DataFrame*) – Data frame containing information about peak loads

Returns *pandas.DataFrame* – Data frame with an additional column with voltage level

`insert_osm_ind_load`()
Inserts electrical industry loads assigned to osm landuse areas to the database.

Returns *None.*

`insert_sites_ind_load`()
Inserts electrical industry loads assigned to osm landuse areas to the database.

Returns *None.*

The central module containing all code dealing with the spatial distribution of industrial electricity demands. Industrial demands from DemandRegio are distributed from nuts3 level down to osm landuse polygons and/or industrial sites also identified within this processing step bringing three different inputs together.

`class DemandCurvesOsmIndustry`(***kwargs*)
Bases: `sqlalchemy.ext.declarative.api.Base`

`bus`

`p_set`

`scn_name`

class DemandCurvesOsmIndustryIndividual(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

demand

osm_id

p_set

peak_load

scn_name

voltage_level

class DemandCurvesSitesIndustry(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus

p_set

scn_name

wz

class DemandCurvesSitesIndustryIndividual(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

demand

p_set

peak_load

scn_name

site_id

voltage_level

wz

class EgonDemandRegioOsmIndElectricity(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

demand

id

osm_id

scenario

wz

class EgonDemandRegioSitesIndElectricity(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

demand

industrial_sites_id

scenario

wz

class IndustrialDemandCurves(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

create_tables()
Create tables for industrial sites and distributed industrial demands :returns: *None.*

industrial_demand_distr()
Distribute electrical demands for industry to osm landuse polygons and/or industrial sites, identified earlier in the process. The demands per subsector on nuts3-level from demandregio are distributed linearly to the area of the corresponding landuse polygons or evenly to identified industrial sites.

Returns *None.*

10.5.45 loadarea

OSM landuse extraction and load areas creation.

class LoadArea(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Creates load area data based on OSM and census data.

Dependencies

- *OsmLanduse*
- *ZensusVg250*
- *HouseholdElectricityDemand*
- *get_building_peak_loads*
- *CtsDemandBuildings*
- *IndustrialDemandCurves*

Resulting tables

- demand.egon_loadarea is created and filled (no associated Python class)

Create and update the *demand.egon_loadarea* table with new data, based on OSM and census data. Among other things, area updates are carried out, smaller load areas are removed, center calculations are performed, and census data are added. Statistics for various OSM sectors are also calculated and inserted. See also documentation section load-areas-ref for more information.

Note: industrial demand contains:

- voltage levels 4-7
- only demand from ind. sites+osm located in LA!

name: str = 'LoadArea'

version: str = '0.0.1'

class OsmLanduse(*dependencies*)
Bases: egon.data.datasets.Dataset

OSM landuse extraction.

- Landuse data is extracted from OpenStreetMap: residential, retail, industrial, Agricultural
- Data is cut with German borders (VG 250), data outside is dropped
- Invalid geometries are fixed
- Results are stored in table *openstreetmap.osm_landuse*

Note: industrial demand contains:

- voltage levels 4-7
- only demand from ind. sites+osm located in LA!

name: str = 'OsmLanduse'

version: str = '0.0.0'

class OsmPolygonUrban(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table openstreetmap.osm_landuse.

area_ha

geom

id

name

osm_id

sector

sector_name

tags

vg250

census_cells_melt()
Melt all census cells: buffer, union, unbuffer

create_landuse_table()
Create tables for landuse data :returns: *None.*

drop_temp_tables()

execute_sql_script(*script*)
Execute SQL script

Parameters **script** (*str*) – Filename of script

loadareas_add_demand_cts()
Adds consumption and peak load to load areas for CTS

loadareas_add_demand_hh()
Adds consumption and peak load to load areas for households

loadareas_add_demand_ind()
Adds consumption and peak load to load areas for industry

loadareas_create()
Create load areas from merged OSM landuse and census cells:

- Cut Loadarea with MV Griddistrict
- Identify and exclude Loadarea smaller than 100m^2.
- Generate Centre of Loadareas with Centroid and PointOnSurface.
- Calculate population from Census 2011.
- Cut all 4 OSM sectors with MV Griddistricts.
- Calculate statistics like NUTS and AGS code.
- Check for Loadareas without AGS code.

osm_landuse_census_cells_melt()
Melt OSM landuse areas and census cells

osm_landuse_melt()
Melt all OSM landuse areas by: buffer, union, unbuffer

10.5.46 low_flex_scenario

The central module to create low flex scenarios

class LowFlexScenario(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

10.5.47 osm

The central module containing all code dealing with importing OSM data.

This module either directly contains the code dealing with importing OSM data, or it re-exports everything needed to handle it. Please refrain from importing code from any modules below this one, because it might lead to unwanted behaviour.

If you have to import code from a module below this one because the code isn't exported from this module, please file a bug, so we can fix this.

class OpenStreetMap(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Downloads OpenStreetMap data from Geofabrik and writes it to database.

Dependencies

- *Setup*

Resulting Tables

- openstreetmap.osm_line is created and filled (table has no associated python class)

- openstreetmap.osm_nodes is created and filled (table has no associated python class)
- openstreetmap.osm_point is created and filled (table has no associated python class)
- openstreetmap.osm_polygon is created and filled (table has no associated python class)
- openstreetmap.osm_rels is created and filled (table has no associated python class)
- openstreetmap.osm_roads is created and filled (table has no associated python class)
- openstreetmap.osm_ways is created and filled (table has no associated python class)

See documentation section osm-ref for more information.

name: `str = 'OpenStreetMap'`

version: `str = '0.0.4'`

add_metadata()
Writes metadata JSON string into table comment.

download()
Download OpenStreetMap *.pbf* file.

modify_tables()
Adjust primary keys, indices and schema of OSM tables.

- The Column "id" is added and used as the new primary key.
- Indices (GIST, GIN) are reset
- The tables are moved to the schema configured as the "output_schema".

to_postgres(*cache_size=4096*)
Import OSM data from a Geofabrik *.pbf* file into a PostgreSQL database.

Parameters **cache_size** (*int, optional*) – Memory used during data import

10.5.48 osm_buildings_streets

Filtering and preprocessing of buildings, streets and amenities from OpenStreetMap

class OsmBuildingsStreets(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Filter and preprocess buildings, streets and amenities from OpenStreetMap (OSM).

This dataset on buildings and amenities is required by several tasks in the pipeline, such as the distribution of household demand profiles or PV home systems to buildings. This data is enriched by population and apartments from Zensus 2011. Those derived datasets and the data on streets will be used in the DIstribution Network Generat0r ding0 e.g. to cluster loads and create low voltage grids.

Dependencies

- *OpenStreetMap*
- *ZensusMiscellaneous*

Resulting Tables

- openstreetmap.osm_buildings is created and filled (table has no associated python class)
- openstreetmap.osm_buildings_filtered is created and filled (table has no associated python class)
- openstreetmap.osm_buildings_residential is created and filled (table has no associated python class)

- openstreetmap.osm_amenities_shops_filtered is created and filled (table has no associated python class)
- openstreetmap.osm_buildings_with_amenities is created and filled (table has no associated python class)
- openstreetmap.osm_buildings_without_amenities is created and filled (table has no associated python class)
- openstreetmap.osm_amenities_not_in_buildings is created and filled (table has no associated python class)
- openstreetmap.osm_ways_preprocessed is created and filled (table has no associated python class)
- openstreetmap.osm_ways_with_segments is created and filled (table has no associated python class)
- boundaries.egon_map_zensus_buildings_filtered is created and filled (table has no associated python class)
- boundaries.egon_map_zensus_buildings_residential is created and filled (table has no associated python class)
- openstreetmap.osm_buildings is created and filled (table has no associated python class)

Details and Steps

- Extract buildings and filter using relevant tags, e.g. residential and commercial, see script *osm_buildings_filter.sql* for the full list of tags. Resulting tables: * All buildings: *openstreetmap.osm_buildings* * Filtered buildings: *openstreetmap.osm_buildings_filtered* * Residential buildings: *openstreetmap.osm_buildings_residential*
- Extract amenities and filter using relevant tags, e.g. shops and restaurants, see script *osm_amenities_shops_preprocessing.sql* for the full list of tags. Resulting table: *openstreetmap.osm_amenities_shops_filtered*
- Create a mapping table for building's osm IDs to the Zensus cells the building's centroid is located in. Resulting tables: * *boundaries.egon_map_zensus_buildings_filtered* (filtered) * *boundaries.egon_map_zensus_buildings_residential* (residential only)
- Enrich each building by number of apartments from Zensus table *society.egon_destatis_zensus_apartment_building_population_per_ha* by splitting up the cell's sum equally to the buildings. In some cases, a Zensus cell does not contain buildings but there's a building nearby which the no. of apartments is to be allocated to. To make sure apartments are allocated to at least one building, a radius of 77m is used to catch building geometries.
- Split filtered buildings into 3 datasets using the amenities' locations: temporary tables are created in script *osm_buildings_temp_tables.sql* the final tables in *osm_buildings_amentities_results.sql*. Resulting tables:
  - Buildings w/ amenities: *openstreetmap.osm_buildings_with_amenities*
  - Buildings w/o amenities: *openstreetmap.osm_buildings_without_amenities*
  - Amenities not allocated to buildings: *openstreetmap.osm_amenities_not_in_buildings*
- Extract streets (OSM ways) and filter using relevant tags, e.g. highway=secondary, see script *osm_ways_preprocessing.sql* for the full list of tags. Additionally, each way is split into its line segments and their lengths is retained. Resulting tables: * Filtered streets: *openstreetmap.osm_ways_preprocessed* * Filtered streets w/ segments: *openstreetmap.osm_ways_with_segments*

```
name: str = 'OsmBuildingsStreets'
```

```
version: str = '0.0.6'
```

```
add_metadata()
```

create_buildings_filtered_all_zensus_mapping()

create_buildings_filtered_zensus_mapping()

create_buildings_residential_zensus_mapping()

create_buildings_temp_tables()

drop_temp_tables()

execute_sql_script(*script*)
Execute SQL script

Parameters **script** (*str*) – Filename of script

extract_amenities()

extract_buildings_filtered_amenities()

extract_buildings_w_amenities()

extract_buildings_wo_amenities()

extract_ways()

filter_buildings()

filter_buildings_residential()

preprocessing()

10.5.49 osmtgmod

substation

The central module containing code to create substation tables

class EgonEhvSubstation(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

bus_id

dbahn

frequency

lat

lon

operator

osm_id

osm_www

point

polygon

power_type

ref

status

subst_name

substation

voltage

class EgonHvmvSubstation(**kwargs)

Bases: sqlalchemy.ext.declarative.api.Base

bus_id

dbahn

frequency

lat

lon

operator

osm_id

osm_www

point

polygon

power_type

ref

status

subst_name

substation

voltage

create_tables()

Create tables for substation data :returns: *None.*

extract()

Extract ehv and hvmv substation from transfer buses and results from osmtgmod

Returns *None.*

class Osmtgmod(*dependencies*)

Bases: *egon.data.datasets.Dataset*

name: str

The name of the Dataset

version: str

The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

import_osm_data()

osmtgmod(*config_database='egon-data'*, *config_basepath='osmTGmod/egon-data'*, *config_continue_run=False*, *filtered_osm_pbf_path_to_file=None*, *docker_db_config=None*)

run()

to_pypsa()

10.5.50 power_etrago

match_ocgt

Module containing the definition of the open cycle gas turbine links

insert_open_cycle_gas_turbines(*scn_name='eGon2035'*)
Insert gas turbine links in egon_etrago_link table.

Parameters **scn_name** (*str*) – Name of the scenario.

Returns *None*

map_buses(*scn_name*)
Map OCGT AC buses to nearest CH4 bus.

Parameters **scn_name** (*str*) – Name of the scenario.

Returns **gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame with connected buses.

The central module containing all code dealing with ocgt in etrago

class OpenCycleGasTurbineEtrago(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

10.5.51 power_plants

assign_weather_data

find_bus_id(*power_plants*, *cfg*)

find_weather_id()
Assign weather data to the weather dependant generators (wind and solar)

Parameters ***No parameters required**

weatherId_and_busId()

write_power_plants_table(*power_plants*, *cfg*, *con*)

conventional

The module containing all code allocating power plants of different conventional technologies (oil, gas, others) based on data from MaStR and NEP.

`match_nep_no_chp`(*nep*, *mastr*, *matched*, *buffer_capacity=0.1*, *consider_location='plz'*, *consider_carrier=True*, *consider_capacity=True*)

Match Power plants (no CHP) from MaStR to list of power plants from NEP

Parameters

- **nep** (*pandas.DataFrame*) – Power plants (no CHP) from NEP which are not matched to MaStR
- **mastr** (*pandas.DataFrame*) – Power plants (no CHP) from MaStR which are not matched to NEP
- **matched** (*pandas.DataFrame*) – Already matched power plants
- **buffer_capacity** (*float, optional*) – Maximum difference in capacity in p.u. The default is 0.1.

Returns

- **matched** (*pandas.DataFrame*) – Matched CHP
- **mastr** (*pandas.DataFrame*) – CHP plants from MaStR which are not matched to NEP
- **nep** (*pandas.DataFrame*) – CHP plants from NEP which are not matched to MaStR

`select_nep_power_plants`(*carrier*)

Select power plants with location from NEP's list of power plants

Parameters **carrier** (*str*) – Name of energy carrier

Returns *pandas.DataFrame* – Waste power plants from NEP list

`select_no_chp_combustion_mastr`(*carrier*)

Select power plants of a certain carrier from MaStR data which excludes all power plants used for allocation of CHP plants.

Parameters **carrier** (*str*) – Name of energy carrier

Returns *pandas.DataFrame* – Power plants from NEP list

mastr

Import MaStR dataset and write to DB tables

Data dump from Marktstammdatenregister (2022-11-17) is imported into the database. Only some technologies are taken into account and written to the following tables:

- PV: table *supply.egon_power_plants_pv*
- wind turbines: table *supply.egon_power_plants_wind*
- biomass/biogas plants: table *supply.egon_power_plants_biomass*
- hydro plants: table *supply.egon_power_plants_hydro*

Handling of empty source data in MaStr dump: * *voltage_level*: inferred based on nominal power (*capacity*) using the ranges from https://redmine.iks.cs.ovgu.de/oe/projects/ego-n/wiki/Definition_of_thresholds_for_voltage_level_assignment which results in True in column *voltage_level_inferred*. Remaining datasets are set to -1 (which only occurs if *capacity* is empty).

- *supply.egon_power_plants_*.bus_id*: set to -1 (only if not within grid districts or no geom available, e.g. for units with nom. power <30 kW)
- *supply.egon_power_plants_hydro.plant_type*: NaN

The data is used especially for the generation of status quo grids by ding0.

import_mastr() → None
Import MaStR data into database

infer_voltage_level(*units_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame
Infer nan values in voltage level derived from generator capacity to the power plants.

Parameters

- **units_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing units with voltage levels from MaStR
- **Returnsunits_gdf** (*gpd.GeoDataFrame*)
- **——-**
- **geopandas.GeoDataFrame** – GeoDataFrame containing units all having assigned a voltage level.

isfloat(*num: str*)
Determine if string can be converted to float. :Parameters: **num** (*str*) – String to parse.

Returns *bool* – Returns True in string can be parsed to float.

zip_and_municipality_from_standort(*standort: str*) → tuple[str, bool]
Get zip code and municipality from Standort string split into a list. :Parameters: **standort** (*str*) – Standort as given from MaStR data.

Returns *str* – Standort with only the zip code and municipality as well a ', Germany' added.

pv_ground_mounted

insert()

pv_rooftop

The module containing all code dealing with pv rooftop distribution to MV grid level.

pv_rooftop_per_mv_grid()
Execute pv rooftop distribution method per scenario

Returns *None.*

pv_rooftop_per_mv_grid_and_scenario(*scenario*, *level*)
Intergate solar rooftop per mv grid district

The target capacity is distributed to the mv grid districts linear to the residential and service electricity demands.

Parameters

- **scenario** (*str, optional*) – Name of the scenario
- **level** (*str, optional*) – Choose level of target values.

Returns *None.*

pv_rooftop_buildings

Distribute MaStR PV rooftop capacities to OSM and synthetic buildings. Generate new PV rooftop generators for scenarios eGon2035 and eGon100RE.

See documentation section pv-rooftop-ref for more information.

class EgonPowerPlantPvRoofBuilding(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table supply.egon_power_plants_pv_roof_building.

building_id

bus_id

capacity

gens_id

index

orientation_primary

orientation_primary_angle

orientation_uniform

scenario

voltage_level

weather_cell_id

class OsmBuildingsFiltered(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table openstreetmap.osm_buildings_filtered.

amenity

area

building

geom

geom_point

id

name

osm_id

tags

class Vg250Lan(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table boundaries.vg250_lan.

ade

ags

ags_0

ars

ars_0

bem

bez

bsg

debkg_id

fk_s3

gen

geometry

gf

ibz

id

nbd

nuts

rs

rs_0

sdv_ars

sdv_rs

sn_g

sn_k

sn_l

sn_r

sn_v1

sn_v2

wsk

add_ags_to_buildings(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*, *municipalities_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Add information about AGS ID to buildings. :Parameters: * **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.

- **municipalities_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame with municipality data.

Returns *gepandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data with AGS ID added.

add_ags_to_gens(*mastr_gdf: geopandas.geodataframe.GeoDataFrame*, *municipalities_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Add information about AGS ID to generators. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame with valid and cleaned MaStR data.

- **municipalities_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame with municipality data.

Returns *gepandas.GeoDataFrame* – GeoDataFrame with valid and cleaned MaStR data with AGS ID added.

add_buildings_meta_data(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*, *prob_dict: dict*, *seed: int*) → geopandas.geodataframe.GeoDataFrame

Randomly add additional metadata to desaggregated PV plants. :Parameters: * **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data with desaggregated PV plants.

- **prob_dict** (*dict*) – Dictionary with values and probabilities per capacity range.
- **seed** (*int*) – Seed to use for random operations with NumPy and pandas.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM building data with desaggregated PV plants.

add_bus_ids_sq(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Add bus ids for status_quo units

Parameters **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data with desaggregated PV plants.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM building data with bus_id per generator.

add_commissioning_date(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*, *start: pandas._libs.tslibs.timestamps.Timestamp*, *end: pandas._libs.tslibs.timestamps.Timestamp*, *seed: int*)

Randomly and linear add start-up date to new pv generators. :Parameters: * **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data with desaggregated PV plants.

- **start** (*pandas.Timestamp*) – Minimum Timestamp to use.
- **end** (*pandas.Timestamp*) – Maximum Timestamp to use.
- **seed** (*int*) – Seed to use for random operations with NumPy and pandas.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data with start-up date added.

add_overlay_id_to_buildings(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*, *grid_federal_state_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Add information about overlay ID to buildings. :Parameters: * **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.

- **grid_federal_state_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame with intersection shapes between counties and grid districts.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data with overlay ID added.

add_weather_cell_id(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

allocate_pv(*q_mastr_gdf: gpd.GeoDataFrame*, *q_buildings_gdf: gpd.GeoDataFrame*, *seed: int*) → tuple[gpd.GeoDataFrame, gpd.GeoDataFrame]

Allocate the MaStR pv generators to the OSM buildings. This will determine a building for each pv generator if there are more buildings than generators within a given AGS. Primarily generators are distributed with the same qunatile as the buildings. Multiple assignment is excluded. :Parameters: * **q_mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded and qcut MaStR data.

- **q_buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing qcut OSM buildings data.
- **seed** (*int*) – Seed to use for random operations with NumPy and pandas.

Returns *tuple with two geopandas.GeoDataFrame s* – GeoDataFrame containing MaStR data allocated to building IDs. GeoDataFrame containing building data allocated to MaStR IDs.

allocate_scenarios(*mastr_gdf: geopandas.geodataframe.GeoDataFrame*, *valid_buildings_gdf: geopandas.geodataframe.GeoDataFrame*, *last_scenario_gdf: geopandas.geodataframe.GeoDataFrame*, *scenario: str*)

Desaggregate and allocate scenario pv rooftop ramp-ups onto buildings. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.

- **valid_buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.
- **last_scenario_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings matched with pv generators from temporally preceding scenario.
- **scenario** (*str*) – Scenario to desaggrgate and allocate.

Returns

tuple –

geopandas.GeoDataFrame GeoDataFrame containing OSM buildings matched with pv generators.

pandas.DataFrame DataFrame containing pv rooftop capacity per grid id.

allocate_to_buildings(*mastr_gdf: gpd.GeoDataFrame*, *buildings_gdf: gpd.GeoDataFrame*) → tuple[gpd.GeoDataFrame, gpd.GeoDataFrame]

Allocate status quo pv rooftop generators to buildings. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing MaStR data with geocoded locations.

- **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data with buildings without an AGS ID dropped.

Returns *tuple with two geopandas.GeoDataFrame s* – GeoDataFrame containing MaStR data allocated to building IDs. GeoDataFrame containing building data allocated to MaStR IDs.

building_area_range_per_cap_range(*mastr_gdf: gpd.GeoDataFrame*, *cap_ranges: list[tuple[int | float, int | float]] | None = None*, *min_building_size: int | float = 10.0*, *upper_quantile: float = 0.95*, *lower_quantile: float = 0.05*) → dict[tuple[int | float, int | float], tuple[int | float, int | float]]

Estimate normal building area range per capacity range. Calculate the mean roof load factor per capacity range from existing PV plants. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.

- **cap_ranges** (*list(tuple(int, int))*) – List of capacity ranges to distinguish between. The first tuple should start with a zero and the last one should end with infinite.
- **min_building_size** (*int, float*) – Minimal building size to consider for PV plants.

- **upper_quantile** (*float*) – Upper quantile to estimate maximum building size per capacity range.
- **lower_quantile** (*float*) – Lower quantile to estimate minimum building size per capacity range.

Returns *dict* – Dictionary with estimated normal building area range per capacity range.

`calculate_building_load_factor`(*mastr_gdf: geopandas.geodataframe.GeoDataFrame*, *buildings_gdf: geopandas.geodataframe.GeoDataFrame*, *rounding: int = 4*) → geopandas.geodataframe.GeoDataFrame

Calculate the roof load factor from existing PV systems. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.

- **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.
- **rounding** (*int*) – Rounding to use for load factor.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing geocoded MaStR data with calculated load factor.

`calculate_max_pv_cap_per_building`(*buildings_gdf: gpd.GeoDataFrame*, *mastr_gdf: gpd.GeoDataFrame*, *pv_cap_per_sq_m: float | int*, *roof_factor: float | int*) → gpd.GeoDataFrame

Calculate the estimated maximum possible PV capacity per building.

Parameters

- **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.
- **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.
- **pv_cap_per_sq_m** (*float, int*) – Average expected, installable PV capacity per square meter.
- **roof_factor** (*float, int*) – Average for PV usable roof area share.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data with estimated maximum PV capacity.

`cap_per_bus_id`(*scenario: str*) → pandas.core.frame.DataFrame

Get table with total pv rooftop capacity per grid district.

Parameters **scenario** (*str*) – Scenario name.

Returns *pandas.DataFrame* – DataFrame with total rooftop capacity per mv grid.

`cap_share_per_cap_range`(*mastr_gdf: gpd.GeoDataFrame*, *cap_ranges: list[tuple[int | float, int | float]] | None = None*) → dict[tuple[int | float, int | float], float]

Calculate the share of PV capacity from the total PV capacity within capacity ranges.

Parameters

- **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.
- **cap_ranges** (*list(tuple(int, int))*) – List of capacity ranges to distinguish between. The first tuple should start with a zero and the last one should end with infinite.

Returns *dict* – Dictionary with share of PV capacity from the total PV capacity within capacity ranges.

`clean_mastr_data`(*mastr_gdf: gpd.GeoDataFrame*, *max_realistic_pv_cap: int | float*, *min_realistic_pv_cap: int | float*, *seed: int*) → gpd.GeoDataFrame

Clean the MaStR data from implausible data.

- Drop MaStR ID duplicates.
- Drop generators with implausible capacities.

Parameters

- **mastr_gdf** (*pandas.DataFrame*) – DataFrame containing MaStR data.
- **max_realistic_pv_cap** (*int or float*) – Maximum capacity, which is considered to be realistic.
- **min_realistic_pv_cap** (*int or float*) – Minimum capacity, which is considered to be realistic.
- **seed** (*int*) – Seed to use for random operations with NumPy and pandas.

Returns *pandas.DataFrame* – DataFrame containing cleaned MaStR data.

`create_scenario_table`(*buildings_gdf*)
Create mapping table pv_unit <-> building for scenario

`desaggregate_pv`(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*, *cap_df: pandas.core.frame.DataFrame*, ***kwargs*) → geopandas.geodataframe.GeoDataFrame
Desaggregate PV capacity on buildings within a given grid district.

Parameters

- **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.
- **cap_df** (*pandas.DataFrame*) – DataFrame with total rooftop capacity per mv grid.

Other Parameters

- **prob_dict** (*dict*) – Dictionary with values and probabilities per capacity range.
- **cap_share_dict** (*dict*) – Dictionary with share of PV capacity from the total PV capacity within capacity ranges.
- **building_area_range_dict** (*dict*) – Dictionary with estimated normal building area range per capacity range.
- **load_factor_dict** (*dict*) – Dictionary with mean roof load factor per capacity range.
- **seed** (*int*) – Seed to use for random operations with NumPy and pandas.
- **pv_cap_per_sq_m** (*float, int*) – Average expected, installable PV capacity per square meter.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM building data with desaggregated PV plants.

`desaggregate_pv_in_mv_grid`(*buildings_gdf: gpd.GeoDataFrame*, *pv_cap: float | int*, ***kwargs*) → gpd.GeoDataFrame
Desaggregate PV capacity on buildings within a given grid district. :Parameters: * **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing buildings within the grid district.

- **pv_cap** (*float, int*) – PV capacity to desaggregate.

Other Parameters

- **prob_dict** (*dict*) – Dictionary with values and probabilities per capacity range.
- **cap_share_dict** (*dict*) – Dictionary with share of PV capacity from the total PV capacity within capacity ranges.
- **building_area_range_dict** (*dict*) – Dictionary with estimated normal building area range per capacity range.

- **load_factor_dict** (*dict*) – Dictionary with mean roof load factor per capacity range.
- **seed** (*int*) – Seed to use for random operations with NumPy and pandas.
- **pv_cap_per_sq_m** (*float, int*) – Average expected, installable PV capacity per square meter.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM building data with desaggregated PV plants.

determine_end_of_life_gens(*mastr_gdf: geopandas.geodataframe.GeoDataFrame*, *scenario_timestamp: pandas._libs.tslibs.timestamps.Timestamp*, *pv_rooftop_lifetime: pandas._libs.tslibs.timedeltas.Timedelta*) → geopandas.geodataframe.GeoDataFrame

Determine if an old PV system has reached its end of life. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.

- **scenario_timestamp** (*pandas.Timestamp*) – Timestamp at which the scenario takes place.
- **pv_rooftop_lifetime** (*pandas.Timedelta*) – Average expected lifetime of PV rooftop systems.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing geocoded MaStR data and info if the system has reached its end of life.

drop_buildings_outside_grids(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Drop all buildings outside of grid areas. :Parameters: **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.

Returns *gepandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data with buildings without an bus ID dropped.

drop_buildings_outside_muns(*buildings_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Drop all buildings outside of municipalities. :Parameters: **buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing OSM buildings data.

Returns *gepandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data with buildings without an AGS ID dropped.

drop_gens_outside_muns(*mastr_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Drop all generators outside of municipalities. :Parameters: **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame with valid and cleaned MaStR data.

Returns *gepandas.GeoDataFrame* – GeoDataFrame with valid and cleaned MaStR data with generatos without an AGS ID dropped.

drop_unallocated_gens(*gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame

Drop generators which did not get allocated.

Parameters **gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing MaStR data allocated to building IDs.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing MaStR data with generators dropped which did not get allocated.

egon_building_peak_loads()

federal_state_data(*to_crs: pyproj.crs.crs.CRS*) → geopandas.geodataframe.GeoDataFrame
Get feder state data from eGo^n Database. :Parameters: **to_crs** (*pyproj.crs.crs.CRS*) – CRS to transform geometries to.

Returns *geopandas.GeoDataFrame* – GeoDataFrame with federal state data.

frame_to_numeric(*df: pd.DataFrame | gpd.GeoDataFrame*) → pd.DataFrame | gpd.GeoDataFrame
Try to convert all columns of a DataFrame to numeric ignoring errors. :Parameters: **df** (*pandas.DataFrame or geopandas.GeoDataFrame*)

Returns *pandas.DataFrame or geopandas.GeoDataFrame*

get_probability_for_property(*mastr_gdf: gpd.GeoDataFrame*, *cap_range: tuple[int | float, int | float]*, *prop: str*) → tuple[np.array, np.array]
Calculate the probability of the different options of a property of the existing PV plants. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.

- **cap_range** (*tuple(int, int)*) – Capacity range of PV plants to look at.
- **prop** (*str*) – Property to calculate probabilities for. String needs to be in columns of mastr_gdf.

Returns

tuple –

numpy.array Unique values of property.

numpy.array Probabilties per unique value.

grid_districts(*epsg: int*) → geopandas.geodataframe.GeoDataFrame
Load mv grid district geo data from eGo^n Database as geopandas.GeoDataFrame. :Parameters: **epsg** (*int*) – EPSG ID to use as CRS.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing mv grid district ID and geo shapes data.

infer_voltage_level(*units_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame
Infer nan values in voltage level derived from generator capacity to the power plants.

Parameters

- **units_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing units with voltage levels from MaStR
- **Returnsunits_gdf** (*gpd.GeoDataFrame*)
- **———-**
- **geopandas.GeoDataFrame** – GeoDataFrame containing units all having assigned a voltage level.

load_building_data()
Read buildings from DB Tables:

- *openstreetmap.osm_buildings_filtered* (from OSM)
- *openstreetmap.osm_buildings_synthetic* (synthetic, created by us)

Use column *id* for both as it is unique hence you concat both datasets. If INCLUDE_SYNTHETIC_BUILDINGS is False synthetic buildings will not be loaded.

Returns *gepandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data with buildings without an AGS ID dropped.

load_mastr_data()
Read PV rooftop data from MaStR CSV Note: the source will be replaced as soon as the MaStR data is available in DB. :returns: *geopandas.GeoDataFrame* – GeoDataFrame containing MaStR data with geocoded locations.

mastr_data(*index_col: str | int | list[str] | list[int]*) → gpd.GeoDataFrame
Read MaStR data from database.

Parameters **index_col** (*str, int or list of str or int*) – Column(s) to use as the row labels of the DataFrame.

Returns *pandas.DataFrame* – DataFrame containing MaStR data.

mean_load_factor_per_cap_range(*mastr_gdf: gpd.GeoDataFrame*, *cap_ranges: list[tuple[int | float, int | float]] | None = None*) → dict[tuple[int | float, int | float], float]
Calculate the mean roof load factor per capacity range from existing PV plants. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.

- **cap_ranges** (*list(tuple(int, int))*) – List of capacity ranges to distinguish between. The first tuple should start with a zero and the last one should end with infinite.

Returns *dict* – Dictionary with mean roof load factor per capacity range.

municipality_data() → geopandas.geodataframe.GeoDataFrame
Get municipality data from eGo^n Database. :returns: *gepandas.GeoDataFrame* – GeoDataFrame with municipality data.

osm_buildings(*to_crs: pyproj.crs.crs.CRS*) → geopandas.geodataframe.GeoDataFrame
Read OSM buildings data from eGo^n Database. :Parameters: **to_crs** (*pyproj.crs.crs.CRS*) – CRS to transform geometries to.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data.

overlay_grid_districts_with_counties(*mv_grid_district_gdf: geopandas.geodataframe.GeoDataFrame*, *federal_state_gdf: geopandas.geodataframe.GeoDataFrame*) → geopandas.geodataframe.GeoDataFrame
Calculate the intersections of mv grid districts and counties. :Parameters: * **mv_grid_district_gdf** (*gpd.GeoDataFrame*) – GeoDataFrame containing mv grid district ID and geo shapes data.

- **federal_state_gdf** (*gpd.GeoDataFrame*) – GeoDataFrame with federal state data.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data.

probabilities(*mastr_gdf: gpd.GeoDataFrame*, *cap_ranges: list[tuple[int | float, int | float]] | None = None*, *properties: list[str] | None = None*) → dict
Calculate the probability of the different options of properties of the existing PV plants. :Parameters: * **mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing geocoded MaStR data.

- **cap_ranges** (*list(tuple(int, int))*) – List of capacity ranges to distinguish between. The first tuple should start with a zero and the last one should end with infinite.
- **properties** (*list(str)*) – List of properties to calculate probabilities for. Strings need to be in columns of mastr_gdf.

Returns *dict* – Dictionary with values and probabilities per capacity range.

pv_rooftop_to_buildings()
Main script, executed as task

scenario_data(*carrier: str = 'solar_rooftop'*, *scenario: str = 'eGon2035'*) → pandas.core.frame.DataFrame
Get scenario capacity data from eGo^n Database. :Parameters: * **carrier** (*str*) – Carrier type to filter table by.

- **scenario** (*str*) – Scenario to filter table by.

Returns *geopandas.GeoDataFrame* – GeoDataFrame with scenario capacity data in GW.

sort_and_qcut_df(*df: pd.DataFrame | gpd.GeoDataFrame*, *col: str*, *q: int*) → pd.DataFrame | gpd.GeoDataFrame

Determine the quantile of a given attribute in a (Geo)DataFrame. Sort the (Geo)DataFrame in ascending order for the given attribute. :Parameters: * **df** (*pandas.DataFrame or geopandas.GeoDataFrame*) – (Geo)DataFrame to sort and qcut.

- **col** (*str*) – Name of the attribute to sort and qcut the (Geo)DataFrame on.
- **q** (*int*) – Number of quantiles.

Returns *pandas.DataFrame or gepandas.GeoDataFrame* – Sorted and qcut (Geo)DataFrame.

synthetic_buildings(*to_crs: pyproj.crs.crs.CRS*) → geopandas.geodataframe.GeoDataFrame

Read synthetic buildings data from eGo^n Database. :Parameters: **to_crs** (*pyproj.crs.crs.CRS*) – CRS to transform geometries to.

Returns *geopandas.GeoDataFrame* – GeoDataFrame containing OSM buildings data.

timer_func(*func*)

validate_output(*desagg_mastr_gdf: pd.DataFrame | gpd.GeoDataFrame*, *desagg_buildings_gdf: pd.DataFrame | gpd.GeoDataFrame*) → None

Validate output.

- Validate that there are exactly as many buildings with a pv system as there are pv systems with a building
- Validate that the building IDs with a pv system are the same building IDs as assigned to the pv systems
- Validate that the pv system IDs with a building are the same pv system IDs as assigned to the buildings

Parameters

- **desagg_mastr_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing MaStR data allocated to building IDs.
- **desagg_buildings_gdf** (*geopandas.GeoDataFrame*) – GeoDataFrame containing building data allocated to MaStR IDs.

wind_farms

generate_map()

Generates a map with the position of all the wind farms

Parameters ***No parameters required**

generate_wind_farms()

Generate wind farms based on existing wind farms.

Parameters ***No parameters required**

insert()

Main function. Import power objectives generate results calling the functions “generate_wind_farms” and “wind_power_states”.

Parameters ***No parameters required**

wind_power_states(*state_wf*, *state_wf_ni*, *state_mv_districts*, *target_power*, *scenario_year*, *source*, *fed_state*)
Import OSM data from a Geofabrik *.pbf* file into a PostgreSQL database.

Parameters

- **state_wf** (*geodataframe, mandatory*) – gdf containing all the wf in the state created based on existing wf.
- **state_wf_ni** (*geodataframe, mandatory*) – potential areas in the the state wich don't intersect any existing wf
- **state_mv_districts** (*geodataframe, mandatory*) – gdf containing all the MV/HV substations in the state
- **target_power** (*int, mandatory*) – Objective power for a state given in MW
- **scenario_year** (*str, mandatory*) – name of the scenario
- **source** (*str, mandatory*) – Type of energy genetor. Always "Wind_onshore" for this script.
- **fed_state** (*str, mandatory*) – Name of the state where the wind farms will be allocated

wind_offshore

insert()
Include the offshore wind parks in egon-data. locations and installed capacities based on: NEP2035_V2021_scnC2035

Parameters ***No parameters required**

The central module containing all code dealing with power plant data.

class EgonPowerPlants(***kwargs*)
Bases: `sqlalchemy.ext.declarative.api.Base`

bus_id

carrier

el_capacity

geom

id

scenario

source_id

sources

voltage_level

weather_cell_id

class PowerPlants(*dependencies*)
Bases: *egon.data.datasets.Dataset*

This module creates all electrical generators for different scenarios. It also calculates the weather area for each weather dependent generator.

Dependencies

- *Chp*
- :py:class:`CtsElectricityDemand

<egon.data.datasets.electricity_demand.CtsElectricityDemand>` * *HouseholdElectricityDemand* * mastr_data * *define_mv_grid_districts* * RePotentialAreas * ZensusVg250 * *ScenarioCapacities* * *ScenarioParameters* * *Setup* * substation_extraction * Vg250MvGridDistricts * *ZensusMvGridDistricts*

Resulting tables

- :py:class:`supply.egon_power_plants

<egon.data.datasets.power_plants.EgonPowerPlants>` is filled

name: str = 'PowerPlants'

version: str = '0.0.18'

allocate_conventional_non_chp_power_plants()

allocate_other_power_plants()

assign_bus_id(*power_plants*, *cfg*)
Assigns bus_ids to power plants according to location and voltage level

Parameters **power_plants** (*pandas.DataFrame*) – Power plants including voltage level

Returns **power_plants** (*pandas.DataFrame*) – Power plants including voltage level and bus_id

assign_voltage_level(*mastr_loc*, *cfg*, *mastr_working_dir*)
Assigns voltage level to power plants.

If location data inluding voltage level is available from Marktstammdatenregister, this is used. Otherwise the voltage level is assigned according to the electrical capacity.

Parameters **mastr_loc** (*pandas.DataFrame*) – Power plants listed in MaStR with geometry inside German boundaries

Returns *pandas.DataFrame* – Power plants including voltage_level

assign_voltage_level_by_capacity(*mastr_loc*)

create_tables()
Create tables for power plant data :returns: *None.*

filter_mastr_geometry(*mastr*, *federal_state=None*)
Filter data from MaStR by geometry

Parameters

- **mastr** (*pandas.DataFrame*) – All power plants listed in MaStR
- **federal_state** (*str or None*) – Name of federal state whoes power plants are returned. If None, data for Germany is returned

Returns **mastr_loc** (*pandas.DataFrame*) – Power plants listed in MaStR with geometry inside German boundaries

insert_biomass_plants(*scenario*)
Insert biomass power plants of future scenario

Parameters **scenario** (*str*) – Name of scenario.

Returns *None.*

insert_hydro_biomass()
Insert hydro and biomass power plants in database

Returns *None.*

insert_hydro_plants(*scenario*)
Insert hydro power plants of future scenario.

Hydro power plants are diveded into run_of_river and reservoir plants according to Marktstammdatenregister. Additional hydro technologies (e.g. turbines inside drinking water systems) are not considered.

Parameters **scenario** (*str*) – Name of scenario.

Returns *None.*

scale_prox2now(*df*, *target*, *level='federal_state'*)
Scale installed capacities linear to status quo power plants

Parameters

- **df** (*pandas.DataFrame*) – Status Quo power plants
- **target** (*pandas.Series*) – Target values for future scenario
- **level** (*str, optional*) – Scale per 'federal_state' or 'country'. The default is 'federal_state'.

Returns **df** (*pandas.DataFrame*) – Future power plants

select_target(*carrier*, *scenario*)
Select installed capacity per scenario and carrier

Parameters

- **carrier** (*str*) – Name of energy carrier
- **scenario** (*str*) – Name of scenario

Returns *pandas.Series* – Target values for carrier and scenario

10.5.52 pypsaeursec

The central module containing all code dealing with importing data from the pysa-eur-sec scenario parameter creation

class PypsaEurSec(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

clean_database()
Remove all components abroad for eGon100RE of the database

Remove all components abroad and their associated time series of the datase for the scenario 'eGon100RE'.

Parameters **None**

Returns *None*

neighbor_reduction()

overwrite_H2_pipeline_share()
Overwrite retrofitted_CH4pipeline-to-H2pipeline_share value

Overwrite retrofitted_CH4pipeline-to-H2pipeline_share in the scenario parameter table if p-e-s is run. This function write in the database and has no return.

read_network()

run_pypsa_eur_sec()

10.5.53 re_potential_areas

The central module containing all code dealing with importing data on potential areas for wind onshore and ground-mounted PV.

class EgonRePotentialAreaPvAgriculture(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table supply.egon_re_potential_area_pv_agriculture.

geom

id

class EgonRePotentialAreaPvRoadRailway(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table supply.egon_re_potential_area_pv_road_railway.

geom

id

class EgonRePotentialAreaWind(***kwargs*)
Bases: sqlalchemy.ext.declarative.api.Base

Class definition of table supply.egon_re_potential_area_wind.

geom

id

create_tables()
Create tables for RE potential areas

insert_data()
Insert data into DB

class re_potential_area_setup(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Downloads potential areas for PV and wind power plants from data bundle and writes them to the database.

Dependencies

- *Setup*
- *DataBundle*

Resulting Tables

- *EgonRePotentialAreaPvAgriculture*
- *EgonRePotentialAreaPvRoadRailway*
- *EgonRePotentialAreaWind*

name: str = 'RePotentialAreas'

tasks: *egon.data.datasets.Tasks* = (<function create_tables>, <function insert_data>)

version: str = '0.0.1'

10.5.54 saltcavern

The central module containing all code dealing with bgr data.

This module either directly contains the code dealing with importing bgr data, or it re-exports everything needed to handle it. Please refrain from importing code from any modules below this one, because it might lead to unwanted behaviour.

If you have to import code from a module below this one because the code isn't exported from this module, please file a bug, so we can fix this.

class SaltcavernData(*dependencies*)

Bases: *egon.data.datasets.Dataset*

name: str

The name of the Dataset

version: str

The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

to_postgres()

Write BGR saline structures to database.

10.5.55 scenario_parameters

parameters

The module containing all parameters for the scenario table

annualize_capital_costs(*overnight_costs*, *lifetime*, *p*)

Parameters

- **overnight_costs** (*float*) – Overnight investment costs in EUR/MW or EUR/MW/km
- **lifetime** (*int*) – Number of years in which payments will be made
- **p** (*float*) – Interest rate in p.u.

Returns *float* – Annualized capital costs in EUR/MW/a or EUR/MW/km/a

electricity(*scenario*)

Returns paramaters of the electricity sector for the selected scenario.

Parameters **scenario** (*str*) – Name of the scenario.

Returns **parameters** (*dict*) – List of parameters of electricity sector

gas(*scenario*)

Returns paramaters of the gas sector for the selected scenario.

Parameters **scenario** (*str*) – Name of the scenario.

Returns **parameters** (*dict*) – List of parameters of gas sector

global_settings(*scenario*)
Returns global paramaters for the selected scenario.

Parameters **scenario** (*str*) – Name of the scenario.

Returns **parameters** (*dict*) – List of global parameters

heat(*scenario*)
Returns paramaters of the heat sector for the selected scenario.

Parameters **scenario** (*str*) – Name of the scenario.

Returns **parameters** (*dict*) – List of parameters of heat sector

mobility(*scenario*)
Returns parameters of the mobility sector for the selected scenario.

Parameters **scenario** (*str*) – Name of the scenario.

Returns **parameters** (*dict*) – List of parameters of mobility sector

Notes

For a detailed description of the parameters see module *egon.data.datasets.emobility.motorized_individual_travel*.

read_costs(*df*, *technology*, *parameter*, *value_only=True*)

read_csv(*year*)

The central module containing all code dealing with scenario table.

class EgonScenario(***kwargs*)
Bases: `sqlalchemy.ext.declarative.api.Base`

description

electricity_parameters

gas_parameters

global_parameters

heat_parameters

mobility_parameters

name

class ScenarioParameters(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Create and fill table with central parameters for each scenario

This dataset creates and fills a table in the database that includes central parameters for each scenarios. These parameters are mostly from extrernal sources, they are defined and referenced within this dataset. The table is acced by various datasets to access the parameters for all sectors.

Dependencies

- *Setup*

Resulting tables

- *scenario.egon_scenario_parameters* is created and filled

name: *str* = 'ScenarioParameters'

version: *str* = '0.0.12'

create_table()
Create table for scenarios :returns: *None.*

download_pypsa_technology_data()
Downlad PyPSA technology data results.

get_sector_parameters(*sector*, *scenario=None*)
Returns parameters for each sector as dictionary.

If scenario=None data for all scenarios is returned as pandas.DataFrame. Otherwise the parameters of the specific scenario are returned as a dict.

Parameters

- **sector** (*str*) – Name of the sector. Options are: ['global', 'electricity', 'heat', 'gas', 'mobility']
- **scenario** (*str, optional*) – Name of the scenario. The default is None.

Returns **values** (*dict or pandas.DataFrane*) – List or table of parameters for the selected sector

insert_scenarios()
Insert scenarios and their parameters to scenario table

Returns *None.*

10.5.56 storages

home_batteries

Home Battery allocation to buildings

Main module for allocation of home batteries onto buildings and sizing them depending on pv rooftop system size.

Contents of this module * Creation of DB tables * Allocate given home battery capacity per mv grid to buildings with pv rooftop

systems. The sizing of the home battery system depends on the size of the pv rooftop system and can be set within the *datasets.yml*. Default sizing is 1:1 between the pv rooftop capacity (kWp) and the battery capacity (kWh).

- Write results to DB

Configuration

The config of this dataset can be found in *datasets.yml* in section *home_batteries*.

Scenarios and variations

Assumptions can be changed within the *datasets.yml*.

Only buildings with a pv rooftop systems are considered within the allocation process. The default sizing of home batteries is 1:1 between the pv rooftop capacity (kWp) and the battery capacity (kWh). Reaching the exact value of the allocation of battery capacities per grid area leads to slight deviations from this specification.

Methodology

The selection of buildings is done randomly until a result is reached which is close to achieving the sizing specification.

class EgonHomeBatteries(**kwargs)
Bases: sqlalchemy.ext.declarative.api.Base

building_id

bus_id

capacity

index

p_nom

scenario

targets = {'home_batteries': {'schema': 'supply', 'table': 'egon_home_batteries'}}

allocate_home_batteries_to_buildings()
Allocate home battery storage systems to buildings with pv rooftop systems

create_table(*df*)
Create mapping table home battery <-> building id

get_cbat_pbat_ratio()
Mean ratio between the storage capacity and the power of the pv rooftop system

Returns *int* – Mean ratio between the storage capacity and the power of the pv rooftop system

pumped_hydro

The module containing code allocating pumped hydro plants based on data from MaStR and NEP.

apply_voltage_level_thresholds(*power_plants*)
Assigns voltage level to power plants based on thresholds defined for the egon project.

Parameters **power_plants** (*pandas.DataFrame*) – Power plants and their electrical capacity

Returns *pandas.DataFrame* – Power plants including voltage_level

get_location(*unmatched*)
Gets a geolocation for units which couldn't be matched using MaStR data. Uses geolocator and the city name from NEP data to create longitude and latitude for a list of unmatched units.

Parameters **unmatched** (*pandas.DataFrame*) – storage units from NEP which are not matched to MaStR but containing a city information

Returns

- **unmatched** (*pandas.DataFrame*) – Units for which no geolocation could be identified
- **located** (*pandas.DataFrame*) – Units with a geolocation based on their city information

match_storage_units(*nep*, *mastr*, *matched*, *buffer_capacity=0.1*, *consider_location='plz'*, *consider_carrier=True*, *consider_capacity=True*)
Match storage_units (in this case only pumped hydro) from MaStR to list of power plants from NEP

Parameters

- **nep** (*pandas.DataFrame*) – storage units from NEP which are not matched to MaStR
- **mastr** (*pandas.DataFrame*) – Pstorage_units from MaStR which are not matched to NEP
- **matched** (*pandas.DataFrame*) – Already matched storage_units

- **buffer_capacity** (*float, optional*) – Maximum difference in capacity in p.u. The default is 0.1.

Returns

- **matched** (*pandas.DataFrame*) – Matched CHP
- **mastr** (*pandas.DataFrame*) – storage_units from MaStR which are not matched to NEP
- **nep** (*pandas.DataFrame*) – storage_units from NEP which are not matched to MaStR

`select_mastr_pumped_hydro()`
Select pumped hydro plants from MaStR

Returns *pandas.DataFrame* – Pumped hydro plants from MaStR

`select_nep_pumped_hydro()`
Select pumped hydro plants from NEP power plants list

Returns *pandas.DataFrame* – Pumped hydro plants from NEP list

The central module containing all code dealing with power plant data.

`class EgonStorages(**kwargs)`
Bases: `sqlalchemy.ext.declarative.api.Base`

`bus_id`

`carrier`

`el_capacity`

`geom`

`id`

`scenario`

`source_id`

`sources`

`voltage_level`

`class Storages(dependencies)`
Bases: *egon.data.datasets.Dataset*

`name: str`
The name of the Dataset

`version: str`
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

`allocate_pumped_hydro_eGon100RE()`
Allocates pumped_hydro plants for eGon100RE scenario based on a prox-to-now method applied on allocated pumped-hydro plants in the eGon2035 scenario.

Parameters **None**

Returns *None*

`allocate_pumped_hydro_eGon2035(export=True)`
Allocates pumped_hydro plants for eGon2035 scenario and either exports results to data base or returns as a dataframe

Parameters **export** (*bool*) – Choose if allocated pumped hydro plants should be exported to the data base. The default is True. If export=False a data frame will be returned

Returns **power_plants** (*pandas.DataFrame*) – List of pumped hydro plants in 'eGon2035' scenario

`allocate_pv_home_batteries_to_grids()`

`create_tables()`
Create tables for power plant data :returns: *None.*

`home_batteries_per_scenario(scenario)`
Allocates home batteries which define a lower boundary for extendable battery storage units. The overall installed capacity is taken from NEP for eGon2035 scenario. The spatial distribution of installed battery capacities is based on the installed pv rooftop capacity.

Parameters **None**

Returns *None*

10.5.57 storages_etrago

The central module containing all code dealing with existing storage units for eTraGo.

`class StorageEtrago(dependencies)`
Bases: *egon.data.datasets.Dataset*

`name: str`
The name of the Dataset

`version: str`
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

`extendable_batteries()`

`extendable_batteries_per_scenario(scenario)`

`insert_PHES()`

10.5.58 substation

The central module containing code to create substation tables

`class EgonEhvTransferBuses(**kwargs)`
Bases: `sqlalchemy.ext.declarative.api.Base`

`bus_id`

`dbahn`

`frequency`

`lat`

`lon`

`operator`

`osm_id`

`osm_www`

point

polygon

power_type

ref

status

subst_name

substation

voltage

class EgonHvmvTransferBuses(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

bus_id

dbahn

frequency

lat

lon

operator

osm_id

osm_www

point

polygon

power_type

ref

status

subst_name

substation

voltage

class SubstationExtraction(*dependencies*)

Bases: *egon.data.datasets.Dataset*

name: str

The name of the Dataset

version: str

The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

create_sql_functions()

Defines Postgresql functions needed to extract substation from osm

Returns *None.*

create_tables()
Create tables for substation data :returns: *None*.

transfer_busses()

10.5.59 vg250

The central module containing all code dealing with VG250 data.

This module either directly contains the code dealing with importing VG250 data, or it re-exports everything needed to handle it. Please refrain from importing code from any modules below this one, because it might lead to unwanted behaviour.

If you have to import code from a module below this one because the code isn't exported from this module, please file a bug, so we can fix this.

class Vg250(*dependencies*)
Bases: *egon.data.datasets.Dataset*

Obtains and processes VG250 data and writes it to database.

Original data is downloaded using *download_files()* function and written to database using *to_postgres()* function.

Dependencies No dependencies

Resulting tables

- *boundaries.vg250_gem* is created and filled
- *boundaries.vg250_krs* is created and filled
- *boundaries.vg250_lan* is created and filled
- *boundaries.vg250_rbz* is created and filled
- *boundaries.vg250_sta* is created and filled
- *boundaries.vg250_vwg* is created and filled
- *boundaries.vg250_lan_nuts_id* is created and filled
- *boundaries.vg250_gem_hole* is created and filled
- *boundaries.vg250_gem_valid* is created and filled
- *boundaries.vg250_krs_area* is created and filled
- *boundaries.vg250_lan_union* is created and filled
- *boundaries.vg250_sta_bbox* is created and filled
- *boundaries.vg250_sta_invalid_geometry* is created and filled
- *boundaries.vg250_sta_tiny_buffer* is created and filled
- *boundaries.vg250_sta_union* is created and filled

filename = 'https://daten.gdz.bkg.bund.de/produkte/vg/vg250_ebenen_0101/2020/vg250_01-01.geo84.shape.ebenen.zip'

name: str = 'VG250'

version: str = 'https://daten.gdz.bkg.bund.de/produkte/vg/vg250_ebenen_0101/2020/vg250_01-01.geo84.shape.ebenen.zip-0.0.4'

add_metadata()
Writes metadata JSON string into table comment.

cleaning_and_preperation()
Creates tables and MViews with cleaned and corrected geometry data.

The following table is created:

- boundaries.vg250_gem_clean where municipalities (Gemeinden) that are fragmented are cleaned from ringholes

The following MViews are created:

- boundaries.vg250_gem_hole
- boundaries.vg250_gem_valid
- boundaries.vg250_krs_area
- boundaries.vg250_lan_union
- boundaries.vg250_sta_bbox
- boundaries.vg250_sta_invalid_geometry
- boundaries.vg250_sta_tiny_buffer
- boundaries.vg250_sta_union

download_files()
Download VG250 (Verwaltungsgebiete) shape files.

Data is downloaded from source specified in *datasets.yml* in section *vg250/original_data/source/url* and saved to file specified in *vg250/original_data/target/file*.

nuts_mview()
Creates MView boundaries.vg250_lan_nuts_id.

to_postgres()
Writes original VG250 data to database.

Creates schema boundaries if it does not yet exist. Newly creates all tables specified as keys in *datasets.yml* in section *vg250/processed/file_table_map*.

vg250_metadata_resources_fields()
Returns metadata string for VG250 tables.

10.5.60 zensus

The central module containing all code dealing with importing Zensus data.

class ZensusMiscellaneous(*dependencies*)
Bases: *egon.data.datasets.Dataset*

name: str
The name of the Dataset

version: str
The `Dataset`'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the `Dataset`'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

class ZensusPopulation(*dependencies*)
Bases: egon.data.datasets.Dataset

name: str
The name of the Dataset

version: str
The Dataset's version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the Dataset's date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

adjust_zensus_misc()
Delete unpopulated cells in zensus-households, -buildings and -apartments

Some unpopulated zensus cells are listed in: - egon_destatis_zensus_household_per_ha - egon_destatis_zensus_building_per_ha - egon_destatis_zensus_apartment_per_ha

This can be caused by missing population information due to privacy or other special cases (e.g. holiday homes are listed as buildings but are not permanently populated.) In the following tasks of egon-data, only data of populated cells is used.

Returns *None.*

create_combined_zensus_table()
Create combined table with buildings, apartments and population per cell

Only apartment and building data with acceptable data quality (quantity_q<2) is used, all other data is dropped. For more details on data quality see Zensus docs: https://www.zensus2011.de/DE/Home/Aktuelles/DemografischeGrunddaten.html

If there's no data on buildings or apartments for a certain cell, the value for building_count resp. apartment_count contains NULL.

create_zensus_misc_tables()
Create tables for zensus data in postgres database

create_zensus_pop_table()
Create tables for zensus data in postgres database

download_and_check(*url*, *target_file*, *max_iteration=5*)
Download file from url (http) if it doesn't exist and check afterwards. If bad zip remove file and re-download. Repeat until file is fine or reached maximum iterations.

download_zensus_misc()
Download Zensus csv files on data per hectare grid cell.

download_zensus_pop()
Download Zensus csv file on population per hectare grid cell.

filter_zensus_misc(*filename*, *dataset*)
This block filters lines in the source CSV file and copies the appropriate ones to the destination based on grid_id values.

Parameters

- **filename** (*str*) – Path to input csv-file
- **dataset** (*str, optional*) – Toggles between production (*dataset='Everything'*) and test mode e.g. (*dataset='Schleswig-Holstein'*). In production mode, data covering entire Germany is used. In the test mode a subset of this data is used for testing the workflow.

Returns *str* – Path to output csv-file

filter_zensus_population(*filename*, *dataset*)
This block filters lines in the source CSV file and copies the appropriate ones to the destination based on geometry.

Parameters

- **filename** (*str*) – Path to input csv-file
- **dataset** (*str, optional*) – Toggles between production (*dataset='Everything'*) and test mode e.g. (*dataset='Schleswig-Holstein'*). In production mode, data covering entire Germany is used. In the test mode a subset of this data is used for testing the workflow.

Returns *str* – Path to output csv-file

population_to_postgres()
Import Zensus population data to postgres database

select_geom()
Select the union of the geometries of Schleswig-Holstein from the database, convert their projection to the one used in the CSV file, output the result to stdout as a GeoJSON string and read it into a prepared shape for filtering.

target(*source*, *dataset*)
Generate the target path corresponding to a source path.

Parameters **dataset** (*str*) – Toggles between production (*dataset='Everything'*) and test mode e.g. (*dataset='Schleswig-Holstein'*). In production mode, data covering entire Germany is used. In the test mode a subset of this data is used for testing the workflow.

Returns *Path* – Path to target csv-file

zensus_misc_to_postgres()
Import data on buildings, households and apartments to postgres db

The API for configuring datasets.

class Dataset(*name: 'str'*, *version: 'str'*, *dependencies: 'Dependencies' = ()*, *tasks: 'Tasks' = ()*)
Bases: object

check_version(*after_execution=()*)

dependencies: *egon.data.datasets.Dependencies* = ()
The first task(s) of this *Dataset* will be marked as downstream of any of the listed dependencies. In case of bare *Task*, a direct link will be created whereas for a *Dataset* the link will be made to all of its last tasks.

name: str
The name of the Dataset

tasks: *egon.data.datasets.Tasks* = ()
The tasks of this *Dataset*. A *TaskGraph* will automatically be converted to *Tasks_*.

update(*session*)

version: str
The *Dataset*'s version. Can be anything from a simple semantic versioning string like "2.1.3", to a more complex string, like for example "2021-01-01.schleswig-holstein.0" for OpenStreetMap data. Note that the latter encodes the *Dataset*'s date, region and a sequential number in case the data changes without the date or region changing, for example due to implementation changes.

Dependencies
A dataset can depend on other datasets or the tasks of other datasets.

alias of Iterable[Union[*Dataset*, Callable[[], None], airflow.models.baseoperator.BaseOperator]]

class Model(***kwargs*)

Bases: sqlalchemy.ext.declarative.api.Base

dependencies

epoch

id

name

version

Task

A *Task* is an Airflow Operator or any Callable taking no arguments and returning None. Callables will be converted to Operators by wrapping them in a PythonOperator and setting the task_id to the Callable's __name__, with underscores replaced with hyphens. If the Callable's __module__ attribute contains the string "egon.data.datasets.", the task_id is also prefixed with the module name, followed by a dot and with "egon.data.datasets." removed.

alias of Union[Callable[[], None], airflow.models.baseoperator.BaseOperator]

TaskGraph

A graph of tasks is, in its simplest form, just a single node, i.e. a single *Task*. More complex graphs can be specified by nesting sets and tuples of *TaskGraphs*. A set of *TaskGraphs* means that they are unordered and can be executed in parallel. A tuple specifies an implicit ordering so a tuple of *TaskGraphs* will be executed sequentially in the given order.

alias of Union[Callable[[], None], airflow.models.baseoperator.BaseOperator, Set[*TaskGraph*], Tuple[*TaskGraph*, ...]]

Tasks

A type alias to help specifying that something can be an explicit *Tasks_* object or a *TaskGraph*, i.e. something that can be converted to *Tasks_*.

alias of Union[*Tasks_*, Callable[[], None], airflow.models.baseoperator.BaseOperator, Set[*TaskGraph*], Tuple[*TaskGraph*, ...]]

class Tasks_(*graph: 'TaskGraph'*)

Bases: dict

first: Set[Union[Callable[[], None], airflow.models.baseoperator.BaseOperator]]

graph: Union[Callable[[], None], airflow.models.baseoperator.BaseOperator, Set[*TaskGraph*], Tuple[*TaskGraph*, ...]] = ()

last: Set[Union[Callable[[], None], airflow.models.baseoperator.BaseOperator]]

prefix(*o*)

setup()

Create the database structure for storing dataset information.

10.6 db

assign_gas_bus_id(*dataframe*, *scn_name*, *carrier*)

Assign `bus_id`s to points according to location.

The points are taken from the given *dataframe* and the geometries by which the *bus_id`s are assigned to them are taken from the `grid.egon_gas_voronoi* table.

Parameters

- **dataframe** (*pandas.DataFrame*) – DataFrame cointaining points
- **scn_name** (*str*) – Name of the scenario
- **carrier** (*str*) – Name of the carrier

Returns **res** (*pandas.DataFrame*) – Dataframe including bus_id

check_db_unique_violation(*func*)

Wrapper to catch psycopg's UniqueViolation errors during concurrent DB commits.

Preferrably used with *next_etrago_id()*. Retries DB operation 10 times before raising original exception.

Can be used as a decorator like this:

```
>>> @check_db_unique_violation
... def commit_something_to_database():
...     # commit something here
...    return
...
>>> commit_something_to_database()
```

Examples

Add new bus to eTraGo's bus table:

```
>>> from egon.data import db
>>> from egon.data.datasets.etrago_setup import EgonPfHvBus
...
>>> @check_db_unique_violation
... def add_etrago_bus():
...     bus_id = db.next_etrago_id("bus")
...     with db.session_scope() as session:
...         emob_bus_id = db.next_etrago_id("bus")
...         session.add(
...             EgonPfHvBus(
...                 scn_name="eGon2035",
...                 bus_id=bus_id,
...                 v_nom=1,
...                 carrier="whatever",
...                 x=52,
...                 y=13,
...                 geom="<some_geom>"
...             )
...         )
...         session.commit()
```

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```
...
>>> add_etrago_bus()
```

Parameters **func** (*func*) – Function to wrap

Notes

Background: using *next_etrago_id()* may cause trouble if tasks are executed simultaneously, cf. https://github.com/openego/eGon-data/issues/514

Important: your function requires a way to escape the violation as the loop will not terminate until the error is resolved! In case of eTraGo tables you can use *next_etrago_id()*, see example above.

credentials()
Return local database connection parameters.

Returns *dict* – Complete DB connection information

engine()
Engine for local database.

engine_for(*pid*)

execute_sql(*sql_string*)
Execute a SQL expression given as string.

The SQL expression passed as plain string is convert to a *sqlalchemy.sql.expression.TextClause*.

Parameters **sql_string** (*str*) – SQL expression

execute_sql_script(*script*, *encoding='utf-8-sig'*)
Execute a SQL script given as a file name.

Parameters

- **script** (*str*) – Path of the SQL-script
- **encoding** (*str*) – Encoding which is used for the SQL file. The default is “utf-8-sig”.

Returns *None.*

next_etrago_id(*component*)
Select next id value for components in etrago tables

Parameters **component** (*str*) – Name of component

Returns **next_id** (*int*) – Next index value

Notes

To catch concurrent DB commits, consider to use *check_db_unique_violation()* instead.

select_dataframe(*sql*, *index_col=None*, *warning=True*)
Select data from local database as pandas.DataFrame

Parameters

- **sql** (*str*) – SQL query to be executed.
- **index_col** (*str, optional*) – Column(s) to set as index(MultiIndex). The default is None.

Returns **df** (*pandas.DataFrame*) – Data returned from SQL statement.

select_geodataframe(*sql*, *index_col=None*, *geom_col='geom'*, *epsg=3035*)
Select data from local database as geopandas.GeoDataFrame

Parameters

- **sql** (*str*) – SQL query to be executed.
- **index_col** (*str, optional*) – Column(s) to set as index(MultiIndex). The default is None.
- **geom_col** (*str, optional*) – column name to convert to shapely geometries. The default is 'geom'.
- **epsg** (*int, optional*) – EPSG code specifying output projection. The default is 3035.

Returns **gdf** (*pandas.DataFrame*) – Data returned from SQL statement.

session_scope()
Provide a transactional scope around a series of operations.

session_scoped(*function*)
Provide a session scope to a function.

Can be used as a decorator like this:

```
>>> @session_scoped
... def get_bind(session):
...     return session.get_bind()
...
>>> get_bind()
Engine(postgresql+psycopg2://egon:***@127.0.0.1:59734/egon-data)
```

Note that the decorated function needs to accept a parameter named *session*, but is called without supplying a value for that parameter because the parameter's value will be filled in by *session_scoped*. Using this decorator allows saving an indentation level when defining such functions but it also has other usages.

submit_comment(*json*, *schema*, *table*)
Add comment to table.

We use Open Energy Metadata standard for describing our data. Metadata is stored as JSON in the table comment.

Parameters

- **json** (*str*) – JSON string reflecting comment
- **schema** (*str*) – The target table's database schema
- **table** (*str*) – Database table on which to put the given comment

10.7 metadata

context()
Project context information for metadata

Returns *dict* – OEP metadata conform data license information

generate_resource_fields_from_db_table(*schema*, *table*, *geom_columns=None*)
Generate a template for the resource fields for metadata from a database table.

For details on the fields see field 14.6.1 of Open Energy Metadata standard. The fields *name* and *type* are automatically filled, the *description* and *unit* must be filled manually.

Examples

```
>>> from egon.data.metadata import generate_resource_fields_from_db_table
>>> resources = generate_resource_fields_from_db_table(
...     'openstreetmap', 'osm_point', ['geom', 'geom_centroid']
... )
```

Parameters

- **schema** (*str*) – The target table's database schema
- **table** (*str*) – Database table on which to put the given comment
- **geom_columns** (*list of str*) – Names of all geometry columns in the table. This is required to return Geometry data type for those columns as SQL Alchemy does not recognize them correctly. Defaults to ['geom'].

Returns *list of dict* – Resource fields

`generate_resource_fields_from_sqla_model`(*model*)

Generate a template for the resource fields for metadata from a SQL Alchemy model.

For details on the fields see field 14.6.1 of Open Energy Metadata standard. The fields *name* and *type* are automatically filled, the *description* and *unit* must be filled manually.

Examples

```
>>> from egon.data.metadata import generate_resource_fields_from_sqla_model
>>> from egon.data.datasets.zensus_vg250 import Vg250Sta
>>> resources = generate_resource_fields_from_sqla_model(Vg250Sta)
```

Parameters **model** (*sqlalchemy.ext.declarative.declarative_base()*) – SQLA model

Returns *list of dict* – Resource fields

`license_ccby`(*attribution*)

License information for Creative Commons Attribution 4.0 International (CC-BY-4.0)

Parameters **attribution** (*str*) – Attribution for the dataset incl. © symbol, e.g. '© GeoBasis-DE / BKG'

Returns *dict* – OEP metadata conform data license information

`license_geonutzv`(*attribution*)

License information for GeoNutzV

Parameters **attribution** (*str*) – Attribution for the dataset incl. © symbol, e.g. '© GeoBasis-DE / BKG'

Returns *dict* – OEP metadata conform data license information

`license_odbl`(*attribution*)

License information for Open Data Commons Open Database License (ODbL-1.0)

Parameters **attribution** (*str*) – Attribution for the dataset incl. © symbol, e.g. '© OpenStreetMap contributors'

Returns *dict* – OEP metadata conform data license information

licenses_datenlizenz_deutschland(*attribution*)
License information for Datenlizenz Deutschland

Parameters **attribution** (*str*) – Attribution for the dataset incl. © symbol, e.g. '© GeoBasis-DE / BKG'

Returns *dict* – OEP metadata conform data license information

meta_metadata()
Meta data on metadata

Returns *dict* – OEP metadata conform metadata on metadata

10.8 subprocess

Exensions to Python's subprocess module.

More specifically, this module provides a customized version of subprocess.run(), which always sets *check=True*, *capture_output=True*, enhances the raised exceptions string representation with additional output information and makes it slightly more readable when encountered in a stack trace.

exception CalledProcessError(*returncode*, *cmd*, *output=None*, *stderr=None*)
Bases: subprocess.CalledProcessError

A more verbose version of subprocess.CalledProcessError.

Replaces the standard string representation of a subprocess.CalledProcessError with one that has more output and error information and is formatted to be more readable in a stack trace.

run(**args*, ***kwargs*)
A "safer" version of subprocess.run().

"Safer" in this context means that this version always raises *CalledProcessError* if the process in question returns a non-zero exit status. This is done by setting *check=True* and *capture_output=True*, so you don't have to specify these yourself anymore. You can though, if you want to override these defaults. Other than that, the function accepts the same parameters as subprocess.run().

CHAPTER

ELEVEN

INDICES AND TABLES

- genindex
- modindex
- search

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PYTHON MODULE INDEX

t

v

z

INDEX

A

B

C

D

E

F

G

H

K

L

M

N

O

P

Q

R

S

T

U

V

W

X

Y

Z