3.2. Open Energy Modelling Framework

The Python-based Open Energy Modelling Framework (oemof) offers an accessible library to create various energy system models based on a couple of basic components. Energy systems modelled by oemof are not limited in scope but rather can range from analysing smallest systems like Solar Home System (SHS) to country-wide models of electricity networks. Each model created with oemof can consist of sinks, sources, transformers and storage, all connected through uni-lateral connectors with respective busses.
Oemof has been subject to a couple of publications, of which a few are summarized here. [55] gives a general introduction to its capabilities. [53] compared the framework to other energy system simulation tools. [51] describes micrOgridS, an MG optimization tool based on an unofficial oemof version, and compares its performance with Homer. It finds that oemof results in lower capacities. The tool presented in Section 3.3 builds up on the experience gathered in the latter paper, but sets a greater focus on adaptability and usability.

Building and optimizing energy systems. When building an energy system model with oemof, the system in question has to be defined as a combination of sinks, sources, transformers and storage. They are connected via uni-lateral flows through one or multiple busses. Each component has a number of parameters describing its behaviour and costs are assigned to flows from or to the respective component.
Further information and additional components integrated in oemof can be found in its documentation [56]. Additional constraints, i.e. a minimal renewable share criteria, can be added to the oemof model.
The model is transposed through oemof and Pyomo is a library for python (Pyomo) to a set of linear equations describing flows and related costs. The problem can then be optimized utilizing different solvers, e.g. Gurobi and Cplex. The hereinafter described, programmed and utilized tool was tested for the recommended Coin-or Branch and Cut Solver (cbc solver). The solver minimizes the objective value, in this case, the total system costs for investments and operation. This results in the cost-optimal solution of capacities and dispatch. For that, each bus is balanced out for each time step in the analysed time period.

Built-in limitations of oemof. Oemof has some built-in limitations resulting from its nature of a linear optimization framework: The core of oemof is to model and solve linear optimization problems. Real component behaviour however is often not linear, i.e. charge efficiency is dependent on the State of Charge (SOC) of the battery and diesel generator efficiency is dependent on its current Load Factor (LF). While the assumption of constant efficiencies is a valid simplification for a quick and approximate simulation of an energy system, it also introduces deviations from actual system behaviour.
Some of the simplifications needed for linearization can be met or even avoided with Mixed-Integer Linear Programming (MILP) (comp. also [57]). A build-in example in oemof poses the transformer: As long as its capacity is defined, a transformer is allowed to have a minimal and maximal LF, amongst others implemented through boolean state variables (integers). Another example is the off-set transformer proposed in [51], which enables a linear dependency of fuel consumption based on its LF and thus allows to model variable generator efficiency with a linearization.

When including MILP into an oemof model however, one has to be aware that it can result in local minima being confused for a global minima, i.e. deviate from the global optimal result, and that it can hugely increase optimization time or even lead to a termination during the solving process.
Oemof optimizes the capacities' dispatch to a degree not possible during actual operation: The simulation is based on perfect foresight, i.e. it optimizes all time steps of the linear equation system at once. Therefore, no uncertainty is connected to future demand or generation from renewable sources and as a result, the dispatch of capacities is overly optimized and unrealistic to reach during actual operation: Batteries, for example, would charge and discharge according to perfectly forecasted future irradiation and demand. The optimized capacities, dispatch strategy and in turn system costs or Levelized Costs of Electricity (LCOE) therefore can be underestimating actual values.
With these two major limitations, a system design resulting from a linear optimization problem should not be understood as an actual implementable design. However, it can allow a first assessment and a comparison between different scenarios or project sites.

3.3. An open-source tool for micro grid optimization

While there are MG planning solutions available, they do not meet the requirements of this research's case study. To enable knowledge transfer and ensure free and open science, a MG optimization tool utilizing the oemof, based on Python3, was created. By using an open-source software, it will be possible to modify the code according to future users' needs, including academia and industry. Due to its interface and coding structure, the developed tool can not only be applied to optimize MG systems but various on- or off-grid electricity solutions. It finds the optimal system capacities, their optimal dispatch and evaluates the system's performance and costs. The program's features, structure, used input data and underlying component models are presented in the following sections.

3.3.1. Requirements

For the development of this study's tool, stakeholder requirements were taken into account, as [51] defined a number of desired features and their prioritization for a MG simulation tool based on a workshop organized by the Reiner Lemoine Institut (RLI). The optimization of basic MG components has the highest priority, including components that could be strongly pre-defined like solar energy source, lead-acid and lithium ion batteries or a generic energy source or storage. It should be possible to define multiple diesel generators, Alternating Current (AC) and Direct Current (DC) coupling are desired and inverters should be a part of the system. With less priority, further energy source and storage technologies could be included. Allowing a grid interconnection is of medium priority for the stakeholders.
To answer the research questions addressed by this study, certain requirements towards the simulation emerged: To evaluate the influence of national grid outages on MG design and performance, the tool must be able to model grid interconnection and emulate randomized blackouts. Additionally, the tool has to be able to evaluate batches of potential project sites and perform a sensitivity analysis of different parameters.

Based on the stakeholder and case study's requirements, the simulation tool was developed and coded as a Python tool utilizing oemof [10]. Sector-coupling is not included in the tool. While the code of the simulation tool is not presented here, its component models, features and general structure are explained, also for future prospective users, in the following sections.

3.3.2. Implemented features

The programming process focused on a versatile and adaptable tool structure, enabling future MG planners to modify the simulated energy system to their specific project requirements or research questions. As such, following features were introduced:

- **Versatile application and scenario definition.** Through scenario definitions, a multitude of energy system models (cases) can be defined. The energy system model's capacity and their dispatch are optimized. All energy systems can be simulated that can be reduced to a combination of the following components: AC and/or DC demand, generator, photovoltaic (PV) panels, storage, inverters, rectifiers, wind plant and connection to a national grid.
- **User-friendly interface.** All simulation parameters, project locations and scenarios can be defined within a single excel file. The time series connected to one or multiple project locations can be defined in one or multiple .csv file(s). Even though it is necessary to install Python as well as required packages and execute the tool via a command-line interface (e.g. miniconda), this should enable users without programming experience to use the tool without having to edit any of the provided code.
- **Multitude of input parameters, sensitivity analysis.** Numerous parameters can be defined to characterize the electricity solution to be simulated, including many techno-economical parameters. A sensitivity analysis of any parameter can evaluate its influence on the overall optimization results. The simulation can run for any time period between one day and a year with hourly time steps.
- **Multiple project sites.** Multiple locations with specific time series, e.g. AC or DC demand, renewable generation and grid availability can be defined in the excel template. A location-specific definition of input parameters is possible.
- **Restarting simulations.** Oemof results as well as generated grid availability time series can be saved and used to restart simulations, e.g. if a simulation aborts. This can, especially during a multi-parameter sensitivity analysis, save computing time.
- **Automatically generated graphs.** To visualize the dispatch of the optimized components, it is possible to generate and save graphs displaying the storage's charging process and more importantly the electricity flows, SOC and grid availability of the system. They can be saved as .png files displaying the whole analyzed time period as well as five exemplary days and as time series in .csv files.
- **Output of linear equation system.** Advanced users can save the linear equation system generated through oemof, e.g. to check its validity or solve the equation system with other solvers suitable for Pyomo.
- **Additional constraints.** To ensure technological reliability of the system, a static stability constraint can be applied. A minimal renewable share can also be required.

3.3.3. Simulation tool outline

The developed simulation tool can roughly be divided into five modules: Data collection, data processing, blackout randomization, oemof-aided building and optimization of an energy system model and evaluation. The process is visualized in Figure 3.1.

Data collection. All necessary data is provided or linked within an excel template. Settings, modelled energy systems, techno-economical parameters as well as a number of project sites or sensitivity analysis can be defined here. A list of all parameters that can be provided can be found in Table A.2. For each project site the path to its time series, provided as a csv-file, is linked. It can contain DC or AC demand (kW), specific solar generation (kW/kW$_{p,inst}$), specific wind plant generation (kW/kW$_{inst}$) and a boolean time series indicating grid availability.

Data processing. When starting the tool, all input data is loaded. The data is initialized for each of the project sites and all experiments of the sensitivity analysis are automatically generated. The time series are cut down to the actual evaluated interval length. Specific per-unit present-day costs and annuities for each component, including capital expenditures (CAPEXs) and operational expenditures (OPEXs) occurring over the whole project duration, are calculated.

Blackout randomization. While actual blackout time series require local measurements of e.g. voltage, information on average blackout duration (in hrs) and frequency (per month) are easily available in [14]. Therefore, these values are used in the simulation tool to artificially generate randomized blackout time series. To take into account the volatility of blackouts, they will be introduced as distributed events, in which the average blackout frequency and duration equals the average of the Gaussian distribution with defined standard deviation. First, the number, start times and durations of the blackout events are randomized. From that, a boolean availability vector is created. Each start time is assigned a blackout duration. Blackout events are allowed to overlap, resulting in a deviation from the initially defined average number and duration of blackouts. The blackout time series can be saved to a file and thus be re-used when running other scenarios that should be based on the same conditions.

Building and optimizing the energy system model. Successively, each of the sensitivity analysis' experiments are optimized and evaluated based on each of the cases defined in the excel template. A case can be based on a previous case, i.e. when evaluating how a MG optimized for off-grid operation performs after grid-interconnection, the component capacities can be defined through a a previous simulation.
With the initialized case definitions, it is possible to generate the oemof energy system model from the available components (see Section 3.3.4) and constraints (see Section 3.3.5). With its adaptability, the tool not only allows to simulate MG but also other configurations, e.g. backup batteries. The generated model is translated into a set of linear equations and solved with the cbc solver. The optimization results can be saved and used to restart a simulation.

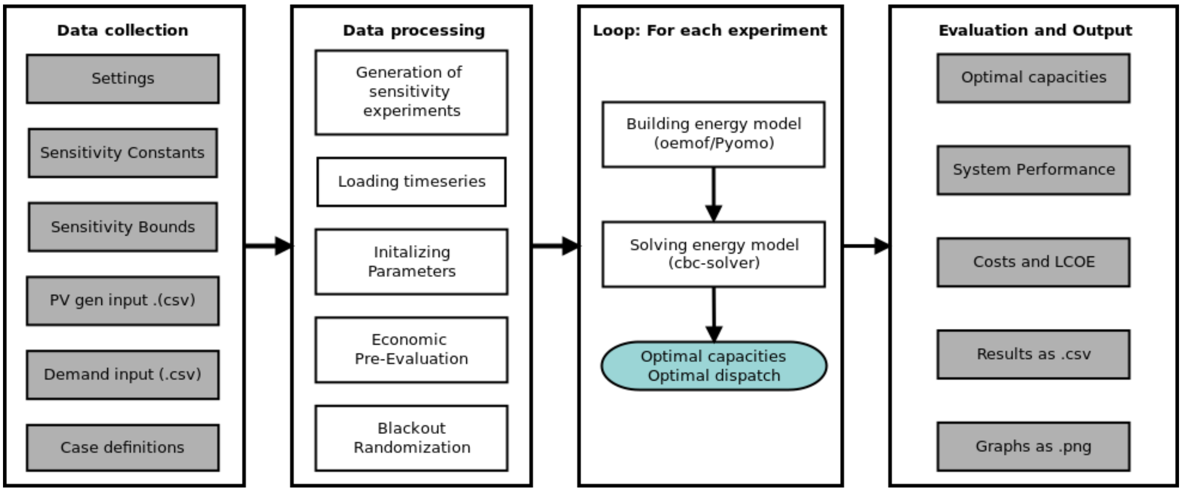

Figure 3.1.: *Simulation tool outline*

Evaluation. The optimized capacities of the energy system's components as well as their dispatch are extracted from the results. The dispatch time series can automatically be visualized and are used to calculate the system's technological performance, including reliability, renewable share and autonomy (see Section 3.3.6). Both optimized capacities and dispatch are used to evaluate LCOE and net present value (NPV) of the system, calculated as described in Section 3.3.7. When optimizing over a short time span, the cost are scaled to a year to adequately reflect the system costs. All performance indicators are calculated for the base year alone: Demand growth is not considered and costs are based on the base year and do not change over time, i.e. no learning curve decreases component prices of replacements. The output saved can be defined through the simulation settings and can consist of all parameter listed in Table A.3.

3.3.4. Energy system and component models

To model and optimize energy systems, and specifically MG's, an AC- as well as DC-bus with a multitude of components are integrated in the tool. A visualization of the tool's structure can be found in Figure 3.2. The components and their technological parameters shall be presented in the proceeding paragraphs.
Connected to the DC-bus are the following components:

- **PV plant**, modelled based on a feed-in time series in $kWh/kW_{p,inst}$. The installed capacity in kW_p can be optimized. Efficiency and system losses are not parameters of the simulation, but rather have to be included in the provided time series.
- **Battery storage**, modeled with a constant throughput-efficiency, maximum charge- and discharge per
- time step defined through attributed C-rates, as well as minimal and maximal SOC. The installed capacity (kWh) and power output (kW) can be optimized.
- **DC demand** as a time series in kWh.
- **Excess** and **shortage** sink required due to oemof-terminology.

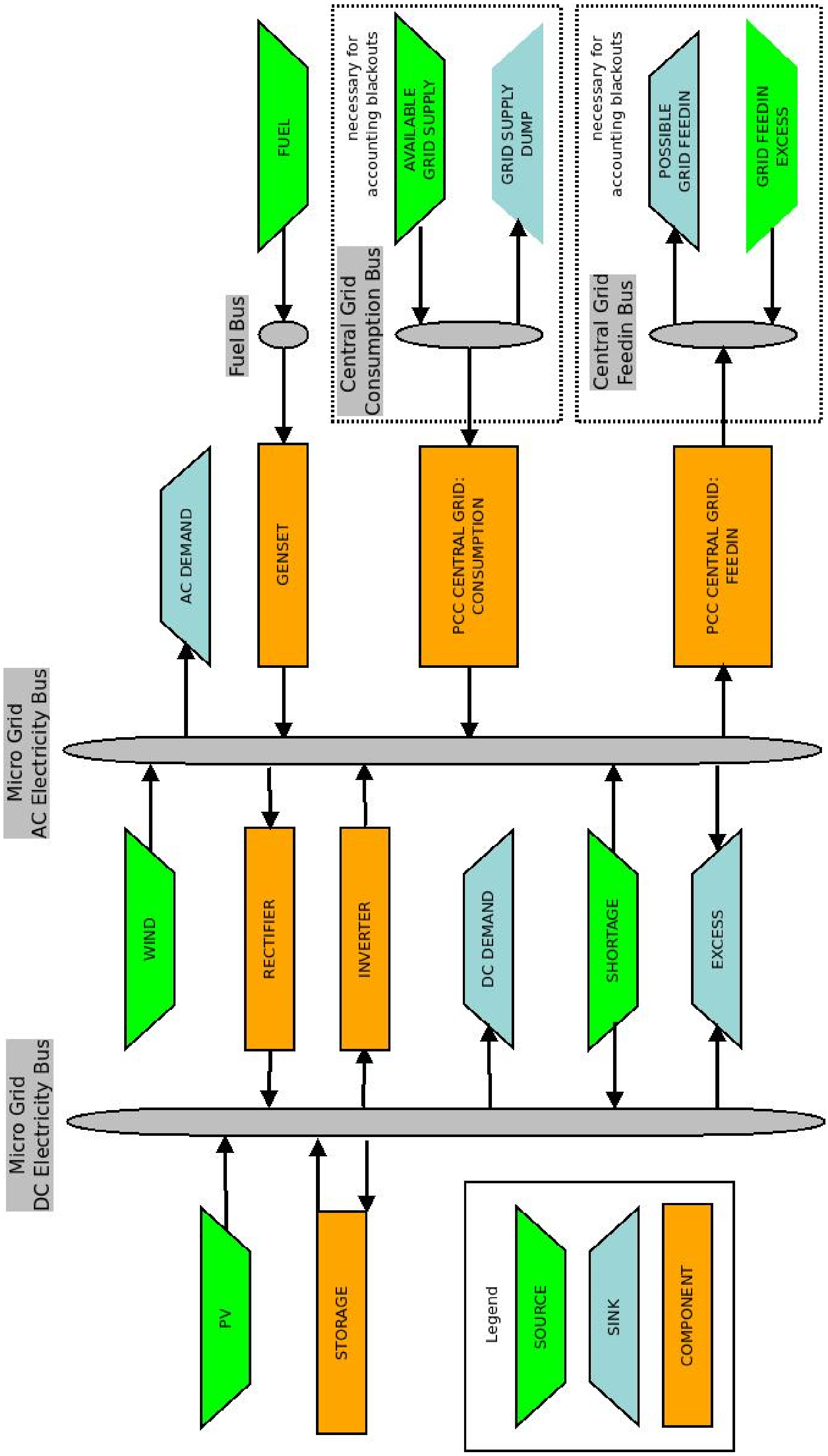

Figure 3.2.: *Adaptable energy system model of the simulation tool*

Using the Open Energy Modelling Framework. Each component can be excluded.

Through a **rectifier** and **inverter** with defined conversion efficiency, the DC- bus is connected to an AC-bus with following components:

- **Wind plant**, modelled based on a feed-in time series in kWh/kW$_{inst}$. The installed capacity kW can be optimized.
- **Generator**, modelled with a constant efficiency and with or without minimal loading. The generator type is determined by the combustion value of the used fuel. The installed capacity in kW can be optimized. The capacity of a generator with minimal loading can not be optimized. Fuel usage is detected trough a fuel source.
- **Point of Common Coupling**, enabling consumption from and/or feed-in to central grid. The installed capacity in kW can be optimized. Costs can either be attributed to the grid operator or the utility grid operator. The Point of Common Coupling (PCC) can allow an electricity flow only when the grid is available. This is defined through a Boolean time series, in which *1* indicates grid availability and *0* an outage.
- **AC demand** as a time series in kWh.
- **Excess** and **shortage** sink required due to oemof-terminology.

It is possible to optimize the dispatch of fixed capacities or to determine the optimal capacities of an energy system with or without connection to a central grid. It is not possible to directly define the used component capacities, apart from the diesel generator and the PCC, both of which can be sized based on a ratio of peak demand.

3.3.5. Additionally introduced constraints

Two constraints are introduced to guarantee technical variability of the optimized system as well as low Greenhouse Gas Emissions (GHG) emissions if a minimal renewable factor is defined.

Stability constraint. As off-grid MGs and grid-connected MGs that islanded due to national grid outage need to ensure stable operation (comp. 2.3.2), a stability constraint is introduced to the simulation tool. They ensure that a certain share of the demand (subtracted by shortage for balancing reasons), the stability limit L_s, is always either met directly through actual supply by the diesel generator P_{DG}, central grid consumption $P_{CG,feedin}$ or is available through potential battery discharge. This translates in two constraints focusing on stored electricity and maximal discharge power of the battery.
The **energy reserve constraint** requires a certain amount of electricity available for discharge through the battery. It can be defined through the current SOC, total battery capacity $CAP_{storage,kWh}$ and minimal battery charge SOC_{min}, but also limited by the allowed discharge rate $Crate$ and discharge ($\eta_{discharge}$) as well as inverter (η_{inv}) efficiencies.

$$\begin{aligned} P_{DG}(t) + P_{pcc,cons} + (SOC(t) - SOC_{min}) \cdot CAP_{storage,kWh} \cdot Crate \cdot \eta_{discharge} \cdot \eta_{inv} \\ >= L_s \cdot (P_D(t) - P_{short}(t)) \quad \forall t \end{aligned} \tag{3.1}$$

Additionally, the optimized discharge power $CAP_{storage,kW}$ has adhere to following **power reserve constraint**:

$$P_{DG}(t) + P_{pcc,cons} + CAP_{storage,kW} \cdot \eta_{inv} >= L_s \cdot (P_D(t) - P_{short}(t)) \quad \forall t \tag{3.2}$$

This constraint is to ensures that renewable generation or demand fluctuations can be met with frequency stabilization measures within the MG. For that, either a diesel generator or a consumption from the national grid through a transformer station can provide spinning reserve. Both are assumed to have a slower reaction time and need to actively contribute to stabilize the system, while batteries only need to have the potential to be sufficiently discharged as they react instantaneously to load changes depending on the control strategy in place. Possible stability-inducing effects of wind-plants are not taken into account.
The constraints are comparable to the spinning reserve constraint defined for the simulation tool used in the research study *Nigeria Rural Electrification Plans* in the scope of the *Nigerian Energy Support Programme* (NESP study) [58] with a stability factor of 20 %. [57] introduces an advanced or spinning reserve constraint based on MILP, requiring generator generation and battery discharge to be able to level out demand and PV variabilities of 25 % each (see [57], equation 7).
The stability constraint should be used when optimizing capacities and dispatch of MG, but is not necessary (or even applicable) when simulating SHS and e.g. the performance of the national grid itself.

Renewable constraint. For future use, it is possible to force MG optimization to determine the capacities that result in a certain minimal renewable share ($L_{res,min}$). It is reversely defined based on the total fossil-fuelled supply, and takes into account that a fraction of the national grid supply might come from renewable sources (RES_{CG}).

$$1 - \frac{\sum_t E_{DG} + (1 - RES_{CG}) \cdot E_{CG,cons}}{E_{gen,total}} >= L_{RES,min} \tag{3.3}$$

3.3.6. Calculation of technical performance indicators

Three main values are used to evaluate and compare the performance of a simulated energy system namely supply reliability as well as renewable and autonomy factor.

- **Supply reliability** η**.** Share of annual supplied electricity E_{spl} and electricity demand E_{dem} of the energy system analysed:

$$\eta = \frac{E_{spl}}{E_{dem}} \tag{3.4}$$

- **Renewable factor** RES**.** Ratio of electricity from renewable sources E_{RE} and fossil-fuelled sources E_{fossil}. The renewable factor of the national grid supply is taken into account.

$$RES = 1 - \frac{E_{fossil}}{E_{fossil} + E_{RE}} = 1 - \frac{E_{gen,DG} + (1 - RES_{CG}) \cdot E_{spl,CG}}{E_{gen,DG} + E_{gen,PV} + E_{gen,Wind} + E_{spl,CG}} \tag{3.5}$$

- **Autonomy factor AF.** Autonomy of an energy system from central grid electricity supply is measured as a ratio of the demand supplied from electricity generated within the MG $E_{spl,MG}$ and the total supplied demand E_{spl}. $E_{spl,MG}$ is calculated by subtracting the consumption from the central grid $E_{spl,CG}$:

$$AF = \frac{E_{spl,MG}}{E_{spl}} = \frac{E_{spl} - E_{spl,CG}}{E_{spl}} \tag{3.6}$$

3.3.7. Calculation of economic performance indicators

The annuity method is used to calculate the economical performance indicators of the evaluated systems (comp. [59, 229ff], [60, 31f]). The evaluation and comparison of the systems can be based on the system's net present value (NPV) and Levelized Costs of Electricity (LCOE). The equations necessary to calculate this parameters are explained below.
There are a number of project specific financial factors:

- Project duration T in years
- Weighted Average Cost of Capital (WACC) $wacc$
- Import tax tax
- Fixed project C_{proj} and distribution grid costs C_{dist}

As described previously, each component is defined through a number of technical as well as economical parameters:

- Investment costs per unit, without import tax c
- Operation and Management (O&M) costs per unit per year $opex$
- Utilization costs per kWh $opex_{wear}$
- Lifetime t

Component costs are central parameters of the optimization problem. As the simulation tool requires per-unit annuities for each component to built the oemof model, the costs have to be preprocessed. From the optimization results, NPV and LCOE can be calculated.

Pre-processing of financial data for optimization problem. Some of the economical values provided to the tool need preprocessing. The first-time investment cost $c_{1st,i}$ of component i is calculated with:

$$c_{1st,i} = c_i \cdot (1 + tax) \tag{3.7}$$

Due to their limited lifetime, k_i replacements are necessary.

$$k_i = round(\frac{T}{t_i} + 0.5) \tag{3.8}$$

Replacements have to be installed in year n within the project lifetime. At the end of the project life, the component has a residual value $c_{res,i}$. It is calculated with the discounted investment costs of the last replacement $c_{last,i}$ and assumed linear depreciation over the asset's lifetime (comp. [59, p. 133]).

$$c_{last,i} = \frac{c_{1st,i}}{(1+wacc)^{(k_i-1)\cdot t_i}} \tag{3.9}$$

$$c_{res,i} = \frac{c_{last,i}}{t_i} \cdot (k_i \cdot t_i - T) \tag{3.10}$$

The CAPEX of the per-unit costs for each component $capex_i$ can thus be calculated with:

$$capex_i = c_i + \sum_k \frac{c_i}{(1+d)^n} - \frac{c_{res,i}}{(1+d)^T} \tag{3.11}$$

The oemof model however uses the annuity of the net present costs of each component. For that the capital recovery factor CRF is introduced, which distributes the present values of the investment costs into annuities for each project year. The inverse of the CRF, the annuity factor a, performs the opposite.

$$CRF = \frac{d \cdot (1+d)^T}{(1+d)^T - 1} \tag{3.12}$$

The annual costs of each component a_i also take into account O&M costs $opex$ per unit and year, but not the specific costs related to component utilization per kWh.

$$a_i = capex_i \cdot CRF + opex_i \tag{3.13}$$

These per-unit annuities for each component as well as their utilization costs per kWh are fed into the oemof model, resulting in optimized capacities and energy flows. If the analysed time period does not span a year, the equivalent fraction of the costs are used. After optimization, this scaling is reversed, so that the resulting costs represent the system's cost over the whole project lifetime.

net present value (NPV) of the optimized system. The optimization problem results in optimized capacities as well as the energy flows E connected to each component. With this information, the component-specific annuities A_i including the utilization costs per kWh $opex_{i,wear}$ can be calculated with

$$A_i = a_i \cdot CAP_i + \sum E \cdot opex_{i,wear} \tag{3.14}$$

Annual cash flows CF are expenditures and revenues linked to different energy flows. They include expenditures for fuel CF_{fuel}, consumption from the central grid $CF_{CG,spl}$ and shortage penalties CF_{short} as well as revenues due to central grid feed-in from the MG $CF_{CG,feedin}$. Their per-unit-value is defined through fuel price, electricity price, shortage penalty costs and

Feed-In Tariff (FIT). Their cash flow in the first year is calculated with their unit-value p_i and accumulated energy flow of volume q_i:

$$CF_i = p_i \cdot q_i \tag{3.15}$$

The net present value of the whole project also includes fixed project, distribution grid and, optionally, central grid extension costs:

$$NPV = \sum_i \frac{A_i}{CRF} + \sum_i \frac{CF_i}{CRF} + NPV_{proj} + NPV_{distr} + NPV_{ext} \tag{3.16}$$

Levelized Costs of Electricity (LCOE). The second economic indicator are the well-known and used LCOE. To reflect the costs of the actual electricity supply, the total system annuity is related to the annual electricity supply. This implies a interdependence between system reliability factor and LCOE, but avoids that unreliable systems are assigned an unreasonable low LCOE solely based on their high intended - but unserved - demand.

$$LCOE = \frac{\sum_i A_i + \sum_i CF_i}{E_{spl}} = \frac{NPV \cdot CRF}{E_{spl}} \tag{3.17}$$