Software-supported investment optimization for district heating supply systems

Felix Panitz, Peter Stange, Tiedo Behrends

Technische Universität Dresden, Chair of Building Energy Systems and Heat Supply,
Dresden (Germany)

Abstract

For district heating or cooling systems the optimal supply system fulfilling the supply task has a high importance. Because of the enormous variety of investment options (kind, amount and size of supply units and storages) the process of finding a cost-optimal set-up of the supply system is very complex. An exemplary system focuses on the right investment decision for an available area. Out of 60 specific generation profiles for solar thermal and photovoltaic plants (with different tilt, azimuth and distance between rows) the optimal set-up and size of several photovoltaic and solar thermal plants are calculated. Even size dependent area demand for heat storage is taken in to account.

Python framework flixOpt is introduced. It supports the process for finding optimal investment decisions for complex supply systems. The framework flixOpt is published open source. Set-up options of flixOpt and challenges to solve complex problems are discussed through the exemplary system. Time series aggregation method is used for reducing computing time.

Keywords: optimization of operation, optimal investment decision, mixed-integer linear programming, MILP, district heating, flixOpt, solar plants, solar thermal, photovoltaic

1. Introduction

Investment decisions for the supply of district heating systems with solar fraction have a very high complexity. The optimal solution means: optimal kind, amount and size of heat and electricity generation units and storages. Usually ‘optimal’ means lowest costs, but often aspects of greenhouse gas emissions and primary energy consumption have to be considered as well.

If solar thermal (ST) or photovoltaic (PV) plants are taken into account, optimal configuration for the given system set-up and heat-demand has to be found. Optimal types and configurations of solar plants should be chosen as well as optimal size of the plants or - if area is limited - optimal usage of a given area.

Mathematical optimization can help in the process of finding this optimum. It gives the theoretical exact solution and finds even intuitively unexpected optimal investment decisions out of the pool of defined options and an optimized operation schedule.

Within this paper an exemplary supply system is considered. The optimal investment option for decarbonizing the system shall be calculated out of a pool of investment possibilities with special focus on solar plants.

The python framework flixOpt for modeling complex energy systems and solving the optimization problem was developed and is applied on the example.

2. Framework flixOpt

2.1 General

FlixOpt is a python framework for modeling and optimizing energy systems via solving mixed-integer programming problems (MILP). It is created for networks of energy flows between so called components like sinks, sources, transforming units and storages. It can also be used for material flows, e.g. ash, water, carbon dioxide.

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FlixOpt development is based on previously used Matlab framework flixOptMat (FAKS, 2019) and has a few influences from package oemof/solph (Krien et al., 2020). FlixOpt is published under MIT license (flixOpt, 2022).

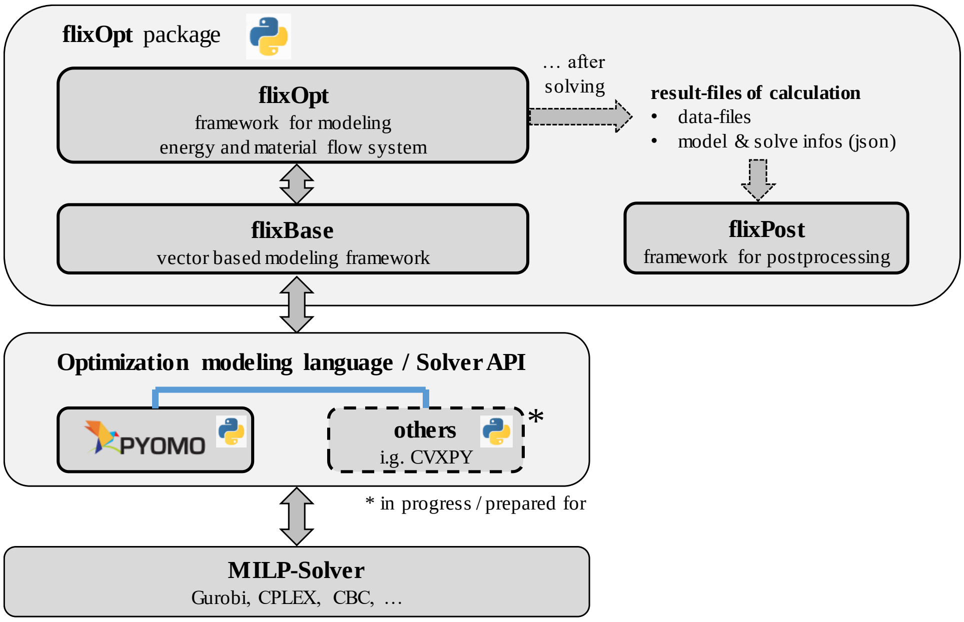


Fig. 1: structure / work flow of flixOpt

It uses pyomo as mathematical optimization modeling language. In preparation for other languages or an own modeling language (as used in flixOptMat) it additionally has a simple intermediate framework flixBase (see Fig. 1). FlixBase actually just provides a vector-variable class and linear equation class for vector based mathematical modeling and transfer to pyomo or to other alternative options.

FlixOpt is developed focusing on fast calculations of energy systems with a high variability in settings like selectable time steps, non-equidistant time steps etc.

A separate python module flixPost provides a simple framework for post-processing of the optimization results.

2.2 Modeling in flixOpt

A flixOpt model consists of buses and components, i.e. transformers, storages, sources and sinks. Each component has input flows and/or output flows. These flows are linked to a node, called ‘bus’, which realizes the flow balance in every time step of all linked flows. Typically, ‘heat’ and ‘electricity’ are common used buses. All details that are relevant for optimization, e.g. costs, efficiency factors, limitations, are implemented as parameters of components and flows.

Boilers, heat pumps, cogeneration units are ‘transformer’ components as one input flow is transformed to one or more output flows. A component of the type transformer can have any number of input and output flows. The (piecewise) linear correlation between the flows is defined within the component.

A component of the type ‘storage’ has one input and one output flow. It can be used to model heat storages as well as batteries, fuel or material storages. It provides several parameters like ‘size of the storage’, ‘fractional loss per hour’, ‘load efficiency’, ‘unload efficiency’ etc.

A component ‘sink’ has only an input flow and can be used to realize demands like a time-resolved heat profile or a feed-in-tariff.

A component of the type ‘source’ has only an output flow and can be used to implement supply tariffs, e.g. for electricity or gas. It is also usable to integrate solar load profiles.

By defining any of the components, the belonging flows have to be defined as well. Flows have many parameters, i.g.

- maximum and minimum load,

- switch-on costs,
- costs per flow-hour (e.g. €/kWh in the case of an electricity tariff),
- maximum full load hours,
- maximum number of switch-on procedures,
- maximum or minimum load factor.

To couple the defined components to a system, every flow has to be linked with the belonging bus.

Usually the optimization target is minimizing the annualized total costs (Stange et al, 2018). But minimizing other aspects like greenhouse gas (GHG) emissions or primary energy consumption must be possible as well.

Costs, emissions etc. are so called ‘effects’ within the scope of flixOpt and are freely definable in any number. Single shares of the defined effects can be parametrized for any component and flow.

Any effect can be defined as the optimization target. The combined use of several effects as optimization target is possible by internalizing: For example, if the effect ‘costs’ is used as the main optimization target and another effect ‘GHG emissions’ is defined, ‘specific costs’ of GHG emissions coupling both effects.

Another possibility to combine targets is to set boundaries, e.g. maximum of permitted primary energy consumption or a limited GHG budget, while finding a cost optimal invest decision for the energy system is the target of optimization. In the following example the effect ‘unbuilt area’ will be defined to consider the limited unbuilt area to realize new supply units.

A theoretically global optimal result is calculated on the basis of the relevant, time-dependent data (demand profiles, prediction of prices etc.) within boundaries of the model accuracy. The result includes not only the optimization target value (e.g. operating costs) but also the optimal operation schedule for all components.

Besides the operational parameters, it is also possible to define the investment as a degree of freedom. In this case the optimization result includes the decision whether or not to invest in a component. Additional to the optimal operation schedule the corresponding optimal investment size is given as a result.

2.3 Time series aggregation in flixOpt

A large number of components and especially a large pool of investment decisions significantly increase the computing time.

For dimensioning of heat-supply and storage units, however, the calculation of an exact, time-resolved operation management plays a subordinate role. In this case, minimizing the sum of annualized investment costs and annual operating costs is of primary importance. This allows the use of the python package TSAM (Hofmann et al., 2020). It provides an optional, automatic time series aggregation to reduce the problem size by a sequence of typical periods described by Welder et al. (2018). First the typical periods and their levelized time series are calculated. Afterwards a reduced model is built to represent the original problem as a sequence of linked typical days. Special focus has to be given to correct implementation of the storage and the transition between periods (Behrends, 2021).

In Behrends (2021) the annual operating costs for a given district heating supply system are computed in a very good approximation in a fraction of the time that is required to solve the non-aggregated problem. This computing time reduction can be up to 90% and thus significantly increases the applicability of the mathematical optimization.

In flixOpt the aggregation method is pragmatically implemented. First the full problem, i.e. variables for every time step, is modelled. Hereby the aggregated (levelized) time series data is used. In the following, optimization time series variables are equalized each time when the typical period occurs where they belong to.

This method significantly increases the amount of equations compared to a slim aggregated model containing each typical period once-only. Due to the equalization it has even more equations than the full non-aggregated problem. But after the pre-solving process by the solver, the number of variables and equations is significantly reduced.

As described before, this pragmatical implementation method uses the identical problem formulation compared to the full model. Therefore, the standard modeling algorithm of the full implementation in flixOpt can be used.

Among other advantages, implementation mistakes of inter-periodical equations are avoided in this way. In case of exceeding the maximum number of variables of the used solver, flixBase could be extended by further pre-solving variable reduction routines.

3. Supply system with solar options

3.1 Basics

A district heating system with nominal load of about 5 MW_{th} has been supplied by an oil boiler and a gas boiler so far. A transformation, i.e. decarbonizing strategy, for the system shall be investigated. For a future supply system several investment options exist and are modeled in flixOpt (Fig. 2).

Details of the preselected pool of investment options are described in table 1. There are two buses, heat and electricity, realizing the energy balance. A heat load profile is given as well as the pump power load profile ('sinks'). Auxiliary electricity demand is considered and depends on the operation of the components.

Regarding the given heat load the supply by new biomass boilers is an option as well as a heat pump and a combined heat and power production (CHP) unit ('transformers'). A heat storage is an invest option to store temporarily surplus energy from the heat sources.

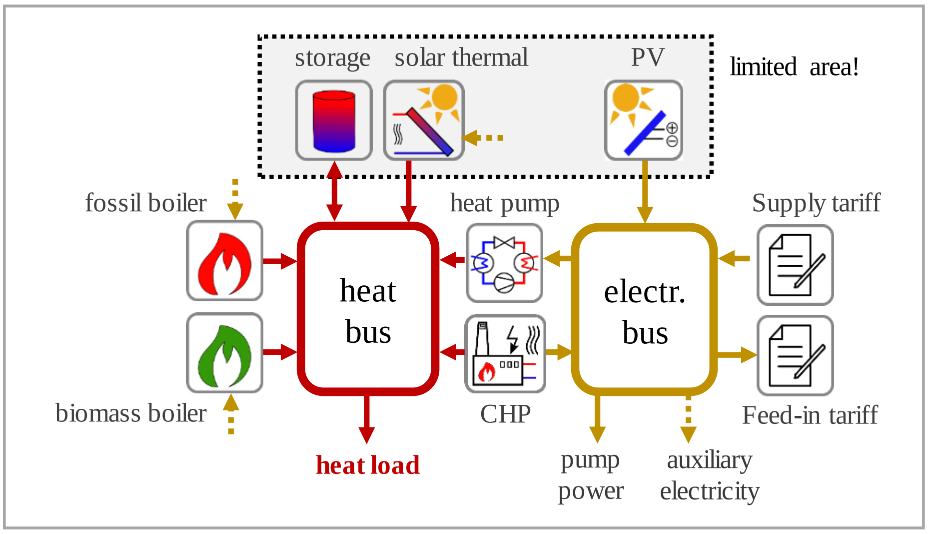


Fig. 2: Exemplary supply system with different invest options of boilers, solar thermal plants and storage

Special focus is given to the usage of a limited unbuilt area, which can be used for the heat storage, solar thermal and photovoltaic plants ('sources').

Besides the effect 'costs' the effect 'unbuilt area' is defined to consider the limited unbuilt area of 20,000 m² in optimization. Consequential specific 'unbuilt area demand' for solar plants and the storage have to be defined. A further effect 'CO_2 emissions' is internalized to the effect 'costs' via the factor of specific costs of CO_2 emissions. The representative investigation period is the year 2019 using hourly time steps.

An extract of the modelled system and used parameters is shown in the following.

Buses and effects:

- buses for electricity and heat
- additional buses for oil, gas and biomass
- 5 effects: costs (optimization target), CO_2 emissions (with specific costs of emissions), unbuilt area (max. 20,000 m²), number of PV plants (max. 3), number of ST plants (max. 3)

Transformers and belonging flows:

- efficiencies, maximal power and minimum partial load for boilers, CHP, heat pump
- switch-on costs for boilers, CHP, heat pump
- specific auxiliary electricity demand for boilers, CHP

Storage:

- specific area demand
- maximal capacity
- fractional loss per hour, efficiency of loading

Sinks/sources and belonging flows:

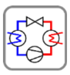
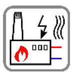
- relative solar profiles for solar plants
- specific floor area demand for solar plants
- specific auxiliary electricity demand for ST plants
- specific costs and CO_2 emissions for flows of oil, gas, electricity-supply, biomass

Annualized investment costs:

- fixed investment costs for CHP-unit and boilers
- fixed and specific investment costs for solar plants, heat-pump, storage and min./max. of investment size.

Annualized investment costs are used as the calculation period is one year.

Table 1: invest options and results of calculation

	invest options	
	**60 ST plant options/ load profiles**	
	tilt	15°, 30°
	azimuth	±90°, ±45°, 0°
	distance between rows (d.b.r.)	1 m to 4 m (steps of 0.5 m)
	Investment options	
	min size	200 m^2_{coll}
	max no. of plants	3
	**60 PV plant options/ load profiles**	
	tilt	15°, 30°
	azimuth	±90°, ±45°, 0°
	distance between rows	1 m to 4 m (steps of 0.5 m)
	Investment options	
	min size	200 m^2_{coll}
	max no. of plants	3
	**heat storage**	
	size	50 m³ to 10,000 m³
	**oil boiler** (existing)	5 MW
	gas boiler (existing)	3 MW
	**biomass boiler 1**	1.5 MW
	biomass boiler 2	2.5 MW
	biomass boiler 3	3.5 MW
	**heat pump**	50 kW to 3,000 kW
	**CHP unit**	68 kW_{el}
	**floor area for storage, ST and PV plants**	
	max Size	20,000 m²

3.2 Solar Profiles

60 specific load profiles -in kilowatt per m² floor area- for each ST and PV in a given range of tilt, azimuth and distance between rows (see table 1) were pre-calculated. This calculation is based on python algorithms by Narusavicius (2022) and further work by the authors. Diffuse and total irradiance data on horizontal surface (DWD, 2022) is converted to tilted surface. In addition, time-resolved ambient, supply and return temperature of the district heating system are used for the calculation of ST yield.

PV plant yield is calculated with pvlib´s (Holmgren et al., 2018) PVWatts model. Default set-up for loss values is used. Additional focus was placed on self-shading of the modules. To recognize non-linear shading effects of PV, the model from Ingenhoven et al. (2019) is applied. Annual yield of the profiles varies from 671 to 935 kWh/kW_{peak}.

ST plant yield is calculated according to simplified model in DIN EN ISO 9806 (2017). Additionally, self-shading is considered. Pipe loss and pipe capacity effects will be added in future. Annual yield of the profiles varies from 442 to 663 kWh/m^2_{coll}.

Initially, the yield, the number of module rows and shading loss is calculated for a quadratic floor area of 1,000 m². The yield is transformed to specific yield per m² module area. Floor area demand per module area differs widely and is considered. Finally, the resulting specific values are used within the optimization process.

In order of practical reasons, the maximum number of realized plants is limited to three PV plants and three ST plants. Considering the maximal available unbuilt area each must have any size greater than 200 m² module area. Taking into account that a higher number of plants possibly cause more planning and installation effort a share of fixed cost is added to every plant.

3.3 Results

The problem is modelled and solved in full and in aggregated form of formulation. For the aggregated model the following time series are considered:

- 60 load profiles of ST plant (weight for aggregation 5/60)
- 60 load profiles of PV plant (weight for aggregation 5/60)
- 1 heat load profile (weight 1)
- 1 coefficient of performance profile of heat pump (weight 1)

The aggregation period is 24 hours. Equal weights for each profile would lead to overweighting the solar profiles due to their number. To obtain acceptable representative periods for all load profiles, the weights for the solar profiles are reduced as shown above. Acceptable aggregated load profiles where found by using 35 typical periods.

In table 2 the results of both models are compared. Both are solved by the solver Gurobi using a gap fraction ≤2.5%. FlixBase counts the variables and equations in the vector based manner as they are defined in the flixBase model. That's why their number seems to be quite small.

Table 2: Comparison of full calculation and aggregated calculation

	full		**aggregated**	
computing time	19 h		1.4 h	
number of…	**variables**	**equations**	**variables**	**equations**
flixBase (vector based)	616	616	616	778
single	1.6e6	1.65e6	1.6e6	2.9e6
single, after pre-solving	290e3 50 % bin	360e3	37e3 56 % bin	50e3
total annual costs	828,000 €		927,000 €	
theoretical lower bound	807,000 €		904,000 €	

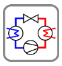
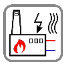
As described in chapter 2.3, the number of equations increases when using the aggregation method. The additional number of equations corresponds to the number of time series variables. However, although the number of single variables for the aggregated model is equal and the number of single equations is quite higher compared to the full model, after pre-solving the number of variables and equations is significantly lower. As a consequence, the computing time is strongly reduced due to the aggregation.

Regarding the total costs and the optimized investment decisions, the aggregated model overestimates the total costs by about 12 %. Either the chosen number of the typical periods (35) is still too low for the solar time series, or the weights of the time series must be revised. Behrends (2021) had realized a better representation of a supply system by the aggregated model even with a lower number of typical periods. However, in Behrends (2021) solar profiles were not part of the system. Concluding, a greater focus on the suitable mapping of the aggregated solar time series is suggested.

Table 3 shows the optimal investment decisions for the system. The aggregated model results in one ST plant and one larger PV plant while the full model results in only one PV plant. Tilt, azimuth and distance between rows are optimized. The storage size is quite equal in both models. In both variants the fossil boilers are removed. The result of the aggregated model includes a second boiler and a small powered heat pump, whereas the result of the full model has a high powered heat pump and a CHP unit. In both results the available unbuilt area is used completely.

In pre-calculations containing very high storage costs results with two or three ST plants with different tilt and azimuth occurred both for aggregated and complete model (Panitz & Stange, 2022). This is a consequence since the simultaneity of yield and load becomes more important if a big storage is not cost-optimal or available.

Table 3: Investment decision results of optimization

	aggregated model		**full model**	
	ST plant tilt 30°, azimuth 0°, d.b.r 1.5 m	3350 m^2_{coll}	-	
	PV plant tilt 15°, azimuth 0°, d.b.r 1.0 m	2 MWp	PV plant tilt 15°, azimuth 0°, d.b.r 1.0 m	2.8 MWp
	668 m³		694 m³	
	removal of oil boiler removal of gas boiler		removal of oil boiler removal of gas boiler	
	bm boiler 1 bm boiler 2	1.5 MW_{th} 2.5 MW_{th}	bm boiler 1	1.5 MW_{th}
	heat pump	0.56 MW_{th}	heat pump	2.37 MW_{th}
	-		CHP unit	68 kW_{el}
	20,000 m²		20,000 m²	

For avoidance of misinterpretation it has to be checked that the result is not a random result in the bandwidth of the admitted fractional solver gap. It is advisable that one additional calculation with just one single south orientated PV plant or one ST plant with typical parameters of tilt and distance between rows should be made. The resulting costs of the multi-plant solution should be lower, otherwise the simple solution should be chosen.

4. Summary

The Python tool flixOpt is an universal open source tool to model and optimize complex energy systems. It was used to optimize a district heating supply system with 120 options of solar plants (each with variable size) and invest options for several other generation units with heat and electricity flows. The framework already provides a wide range of functionality so that there is no need to implement additional equations to model and solve the demonstrated example. Specific yield profiles of the solar plants were pre-calculated via simulations for a representative quadratic floor area of 1,000 m². Self-shading of ST modules and PV modules is considered.

For optimizing the system two approaches of computation are used: one containing the full model and one containing the aggregated model. Aggregation reduces computing time significantly compared to the full model. However, the aggregation has to be used very carefully in combination with solar profiles because results can significantly differ as shown in the given example.

In summary, mathematical optimization supports the decision maker to evaluate different options of solar plants and to calculate optimized size of plants as shown. In the given example only one type of ST collector and PV module is used. Moreover, decision problems with several types of ST collectors or PV modules with different corresponding invest costs and yield characteristics can be of interest in practical issues and can be implemented likewise.

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