Approach for simulation-based scenario analyses of district energy systems

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Abstract:

In many urban contexts, energy systems are undergoing fundamental change as distributed generation of electricity, integration of renewable energy sources, and distribution of thermal energy leads to a more flexible and interconnected system. Appropriate planning tools are necessary in order to guide this transition towards more energy and cost efficient system designs. Thus, the aim of this paper is to present an approach for simulation-based scenario analyses of energy systems on district scale. For this presentation we will focus on the thermal energy supply, distribution, and demand of a university campus with 39 buildings.

In order to evaluate different scenarios of system design and operation, we present a partly automated process to simulate the dynamic system behavior. For data collection and management, we use a Geographic Information System (GIS) coupled with a PostgreSQL database. Information about the building stock is used to parameterize low order building models and simulate each building's heat demand. A network modeling routine written in Python combines these heat demand time series with network information from the database to automatically create a full district energy system model. To facilitate this modeling approach, we designed component models for buildings, substations, pipes, and supply plants in the modeling language Modelica.

For illustration, we evaluated two scenarios. In scenario 1, an optimization led to an improved heating curve, with which yearly primary energy demand in the model was reduced by 7.5 %. In comparison, the retrofitting of all building envelopes in the district energy system for Scenario 2 reduced primary energy demand of the central heat supply by 45.6 %.The example results showed that the presented approach is suited to evaluate different scenarios for reducing primary energy demand of a district energy system, ranging from improved operation to changes in system design, and a combination of both.

Keywords:

District Energy Systems, Energy Efficiency, Modelica, Optimization.

1. Introduction

In many countries the energy supply of buildings accounts for a major share of primary energy demand [1]. In many urban contexts, these energy systems are undergoing fundamental change towards a more flexible and interconnected system. Reasons for such change lie in the increased distributed generation of electricity [2,3], integration of renewable energy sources [4], and the blurring boundaries between systems using different energy forms. These blurring boundaries lead to multi-energy systems, which try to make best use of all available forms of energy including interconnections and transformations between energy forms like electricity, heat, and cooling [5].

Appropriate planning tools are necessary in order to guide this transition towards more energy and cost efficient system designs [6,7]. Yet, one of the major challenges for such planning tools is the system complexity [8,9], which significantly increases with scope and scale of the energy systems analysis. As a result, different approaches for simplification in district energy system analyses have been investigated. In order to simulate and optimize the system, some studies have reduced the number of buildings by lumping similar buildings together as a representative consumer station (see e.g. [10,11]). Also, simulation time can be limited to representative periods, which can be seasonal, monthly or daily (see e.g. [12,13]).

Nevertheless, a detailed dynamic system model could help to prototype different control and management concepts and compare different retrofit options on a district scale. Important challenges on a way to such a model are to provide reliable results and reduce manual effort and computation times. As a contribution towards a dynamic system model, the aim of this paper is to present an approach for simulation-based scenario analyses of district energy systems. For this presentation we will focus on the thermal energy supply, distribution, and demand of a university campus with 39 buildings.

2. District energy system modeling approach

In this chapter, we will present a partly automated process to evaluate different scenarios of district energy system design and operation by simulating the dynamic system behavior. This process involves data collection of the current system design, the creation of a system model for each considered scenario, and the analysis of results from dynamic simulation of the entire system. For data collection and management, we use a Geographic Information System (GIS) coupled with a PostgreSQL database. Basic information about the building stock from this database is used to parameterize low order building models and simulate each building's heat demand. A network modeling routine written in Python combines these heat demand time series with network information from the database to automatically create a full district energy system model. To facilitate this modeling approach, we designed component models for buildings, substations, pipes, and supply plants in the modeling language Modelica. This allows us to fully automate the model parameterization and the system modeling by connecting instances of the modular component models.

2.1. Data collection with GIS

As pointed out above, one problem with the high complexity of district energy systems is the large amount of data necessary to describe the entire system. In order to prevent efforts for collection and management of this data from becoming prohibitively cumbersome, we rely on limiting the amount of data close to a needed minimum and the use of appropriate data management tools. Using a GIS representation of the district creates a user friendly interface to collect and display the data and put it into a spatial context. Coupling the graphical GIS representation of the district with a database system allows for fast access to the data, which helps with automating its analysis and its use in automated modeling routines.

For the presented implementation we use the software tool QGIS for visualization of the city district and as an interface for the data collection process. QGIS is developed open source, freely available and widely used. It offers a wide range of GIS features, among them the possibility to couple it with a PostgreSQL database by means of a software plug-in. As PostgreSQL itself is also an open source project and provides a fully functioning SQL database solution, this coupling provides a powerful data management tool that is freely available and well suited for the application presented in this paper.

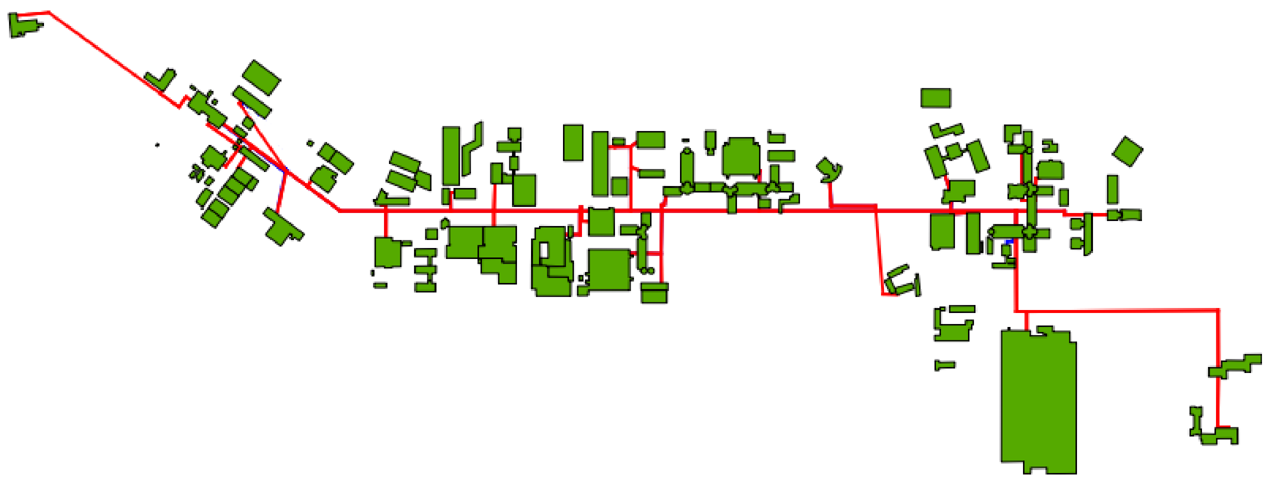

Fig. 1. Graphical GIS representation of the buildings and the district heating network for the investigated university Campus.

The database collects information about the supply plants, buildings, and the network's pipe segments. Another important part of the data is information about the connections between individual components. In order to describe these connections, we use a graph notation, in which each pipe segment is represented by an edge connecting two nodes. Each node represents a location in the district. Thus, buildings, supply plants and pipe junctions are all represented by nodes. The different types of nodes can thus be interpreted as sub-graphs without edges, with each type having a different set of data associated to it.

This data structure allows the user to mark buildings, supply plants, and junctions on the graphical representation of the district in QGIS as nodes and connect these nodes by edges to define pipe locations. By adding information like year of construction to building nodes or length and diameter to the pipe edges, the user can create a functional description of the entire system. As the data is all stored in the SQL database, it can easily be retrieved by automated queries. This approach facilitates the use of data in the automated steps described in the following sections.

2.2. Automated simulation of building heat demands

Buildings' heat demands are a key aspect of a detailed district energy simulation, as these demands determine the system's heat load and thus its dynamic operation. Several building models and software tools are available to simulate a building's heat demand given information about the building and the outdoor conditions. Useful data about the building includes the building's size, heat transfer properties of its envelope, and its patterns of usage. Considering the building stock of a city district, such data is often not available in the required level of detail for each building. Therefore, we use a simplified building model that can be parameterized with available data and assumptions derived from statistical analyses for unknown values.

To model the buildings' heat demand, we implemented the modeling approach described in German guideline VDI 6007 in the modeling language Modelica. The model is freely available and has been described in [14]. For illustration, Fig. 2 shows the resistance-capacitance network with which the buildings thermal energy balance is modeled. In this approach, all outside walls are aggregated into one representative capacitance, which is connected to the outdoor air and the indoor air via one thermal resistance each. All inside walls without connection to the outdoor environment are similarly modeled by one capacitance and a thermal resistance towards the indoor air volume. Inner loads and solar radiation are also connected to this indoor air volume, which by itself also is represented as a thermal capacitance.

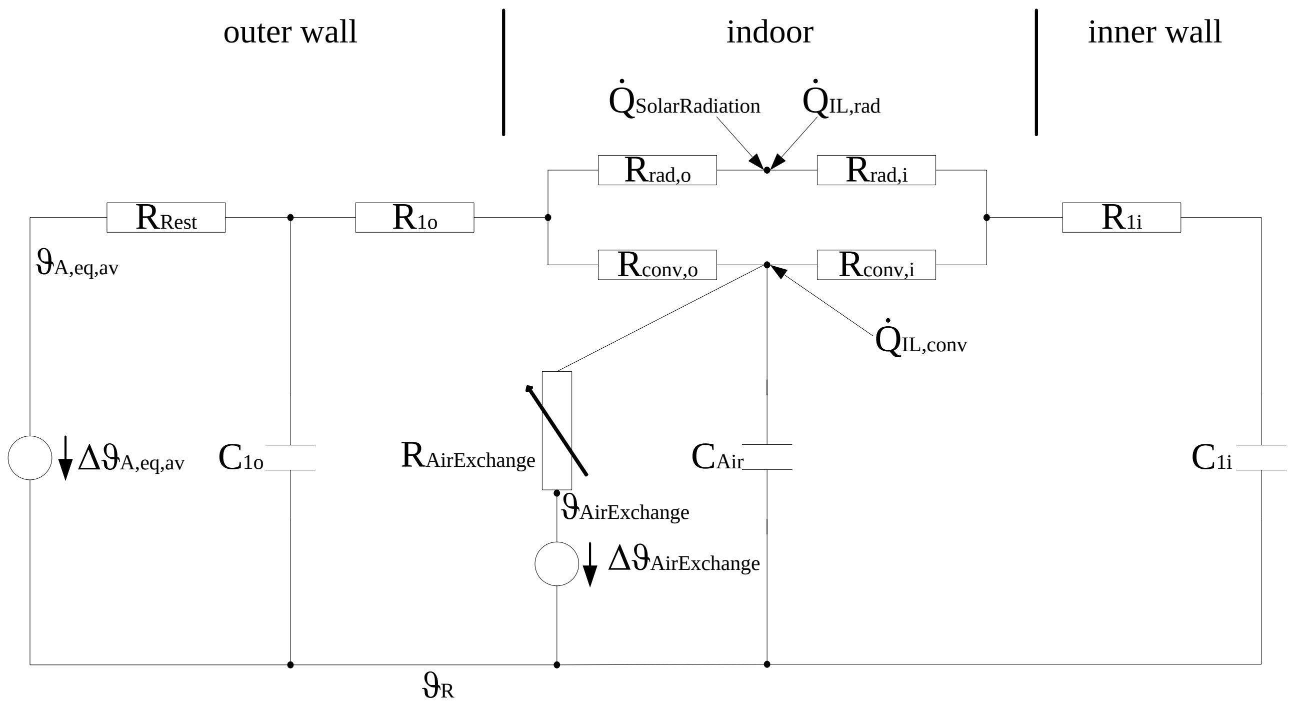

Fig. 2. Network scheme of thermal resistances and capacitances for the simplified building model based on guideline VDI 6007.

The methods to calculate the values of thermal resistances and capacitances from known building properties are given in VDI 6007. If detailed information about a building is available, the building model can be parameterized accordingly. For cases in which this data is not available or incomplete, it is possible to use statistical data about similar buildings to estimate the parameters. In order to automate this process for larger numbers of buildings we use a methodology originally developed for the comparison of retrofit options in office buildings [15]. This methodology requires a minimum input of building usage type (e.g. office or residential building), year of construction or last retrofit, ground area and number of floors. In most cases, this data can be gathered or estimated even for larger numbers of buildings in a city district.

We developed the software tool TEASER programmed in Python which uses this minimum data set either from manual input or from a database query to estimate the building parameters, calculate the respective model parameters, and automatically simulate all buildings of a city district. The estimation of building properties is based on the year of construction and building type, which information is used to access a database of average building properties from national building stock statistics. In order to also model the influence of user behavior and the resulting variations between buildings of a similar building type and year of construction, the inner loads are calculated depending on time series input of user occupancy, electrical equipment use, and lighting schedules. Basic profiles for the time series are taken from the norms DIN 18599 and SIA 204. These static profiles are then stochastically varied by means of Markov chains for each building. Thus, with access to the database described in section 2.1, the software tool can simulate the heat load of an entire city district without further manual effort. An open source release of TEASER is planned for the near future.

2.3. Modeling of network components

For modeling the district energy system, we aim at a solution to provide a holistic dynamic system model with as little manual effort as possible. To facilitate this modeling approach, we designed component models for buildings, substations, pipes, and supply plants in the modeling language

Modelica. Modelica was chosen because its object-oriented and equation-based language design enables to fully automate the model parameterization and the system modeling by connecting instances of the modular component models.

Figure 3 shows a simple example of how the individual component models can be connected to form part of a district energy system model. Some details of the model implementation have been omitted in the figure for reasons of clarity. Each of the component models can itself consist of multiple layers of sub-models. For the supply (red triangle) and the substation (green triangle in box), a scheme of the first sub-model layer is included in the figure. The main parts of the supply model are a pump, which takes as an input a set differential pressure from a differential pressure controller, and the heat generation, which has an input for the set supply temperature determined by another controller. The substation consists of a mass flow control valve and a fluid volume from which heat is extracted. The control valve's opening is determined by the mass flow controller. The heat is extracted according to calculations of heat exchanger behavior with the assumption of fixed secondary side temperatures and the fulfillment of the heat demand as calculated by the building model. A more detailed account of similar substation modeling is given in [16].

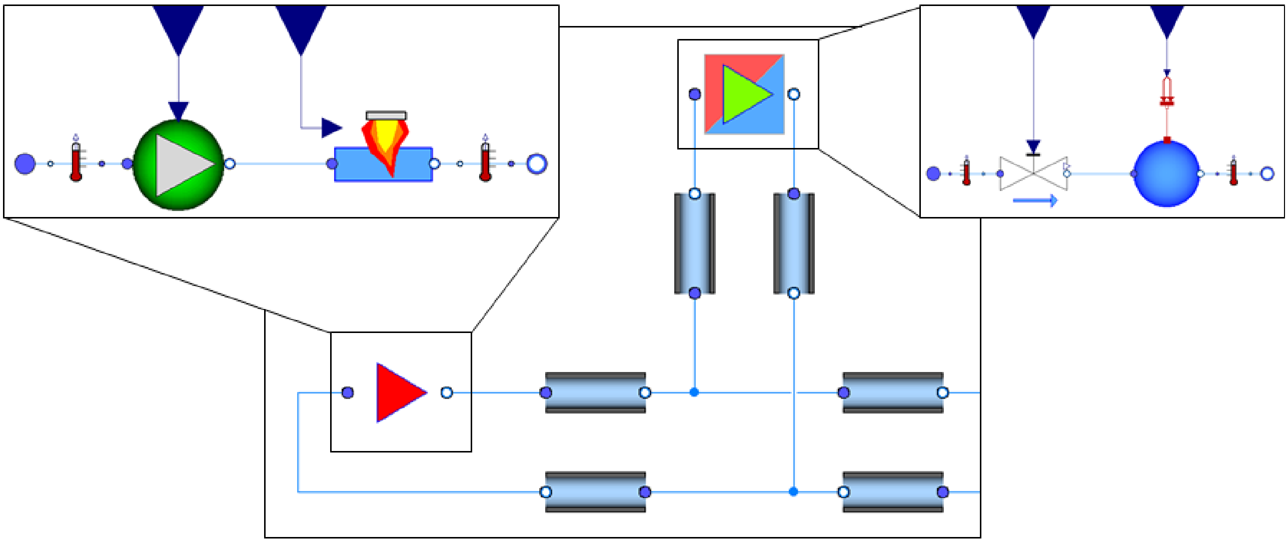

Fig. 3. Scheme of a district energy system model consisting of connected sub-models for supply, pipes, and substation (details have been omitted in this figure for clarity)

All network components are connected by fluid connectors which contain relations for the mass flow rate, the enthalpy and the pressure at a given port. The pipe models are parameterized with values for the pipe length, diameter and insulation level. With this information, they calculate the heat losses, the pressure drop across the pipe and the resulting mass flow rate for each time-step. The overall mass flow in the system is determined by the differential pressure introduced by the pump model in the supply component and each opening of the substations' mass flow control valves. The system's supply temperature is controlled according to a heat curve which determines supply temperatures for given outdoor air temperatures in every time-step. The return temperature with which the fluid returns to the supply unit is the result of all return temperatures fed back to the network from the substation models and the distribution heat losses in the pipes. Thus, this modelling approach is able to provide a full thermo-hydraulic model of the district energy system.

2.4. Automated network modeling

With the component models described in the previous section, it is possible to build a district energy system model using the graphical representation layer of a Modelica software tool by drag-and-dropping the sub-models to a model view window and drawing connections between the ports.

This is an intuitive way of modeling for small systems. Nevertheless, even for mid-sized systems like a university campus the necessary manual effort quickly grows large. For our example district, a university campus with 1 supply plant and 39 buildings, it would be necessary to place and connect around 200 pipe elements and set several hundreds of parameters like pipe lengths and Kv-values for each substation's mass flow control valve. In order to reduce this effort, we developed a Python program which automates the creation of the district energy system model.

In addition to the graphical representation layer, the Modelica language defines each model with code in the form a text file. Thus, it is possible to let a Python routine write this Modelica code given the necessary input information. We use the Python package networkX to manage all needed data in a Python graph format. As described in section 2.1, we collect information about the district energy system in a database and use graph notation to describe the connections of supply plants, buildings, and pipe elements. This enables us to query a list of all nodes and their connection edges from the database and initialize a networkX graph with this information. Each node and edge in the graph can be enriched with data by setting its attributes. Therefore, all information needed for the model generation can efficiently be managed in such a graph object.

When all data is queried from the database and stored in the graph object, Python can loop over the nodes and edges of the graph and write the Modelica code to a model file. As the database is filled with data via the interface of QGIS, information about all nodes' locations is also available. With this information, in the Modelica code annotations to all component models can be made which enable the previously mentioned graphical representation of the system model similar to Fig. 3. This means that later changes to the model can also be made manually in the graphical view of a Modelica software tool. This can be useful when investigating small variations and their effects on the existing system. For larger changes, it is also possible to redraw these in a new layer in QGIS and automatically generate a new system model from the data.

The resulting system model can then be simulated using a Modelica software tool. We currently use the commercial software Dymola, but plan to also use the open source software OpenModelica in the future. These Modelica software tools allow for simulations with different simulation times and time-steps. A further option is to again use Python scripts to automate the simulation of multiple models. For this we use the Python package buildingsPy, which is not only able to automate the simulation of a model but also allows the user to change parameters in the model. With another Python package called ModelicaRes, it is also possible to directly analyze the simulation results after the simulation. This opens up possibilities to write optimization routines which simulate a set of candidate options, analyze the simulation results and go on refining parameters to minimize a given cost function.

3. Description of scenarios

To illustrate the possible uses for the presented modeling approach, we will use RWTH Aachen University's Campus Melaten as an example. Its district heating system supplies 39 research buildings with a hot water pipe network. The large university hospital on site is not considered part of the system because it is supplied by a separate hot water flow at higher temperatures. The district is shown in Fig. 1. A central heating plant seen on the left side of the figure uses gas boilers to supply the heat to the network. For this illustrating example, we assume the boiler efficiency to be $\eta = 0.9$ and the supply temperature following a heating curve which varies the supply temperature between 140 °C and 100 °C depending on the outdoor air temperature. This heating curve is shown in Fig. 4.

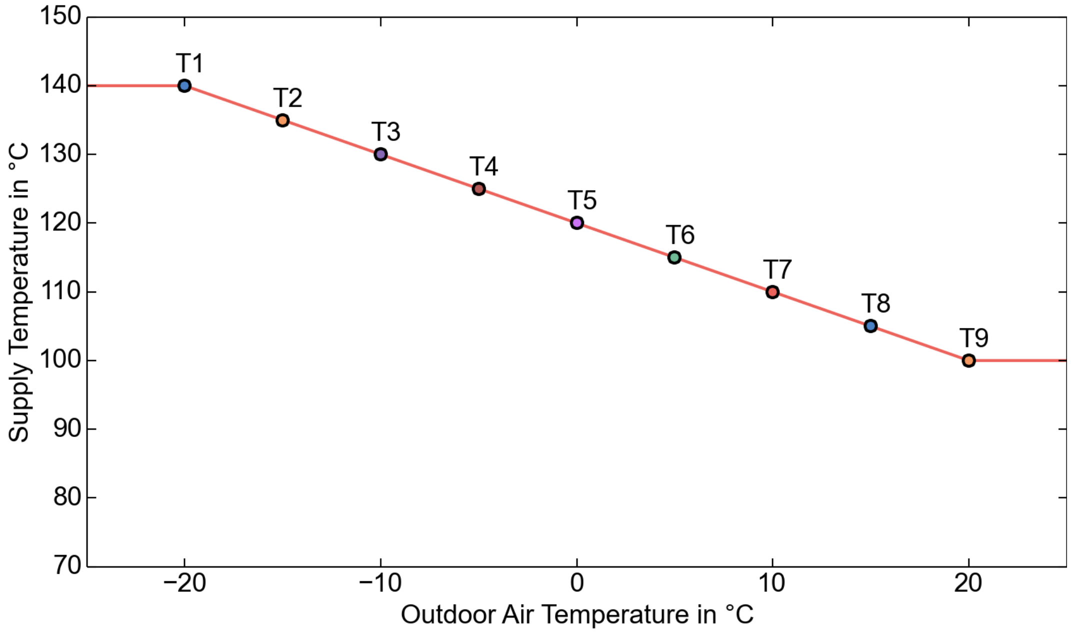

Fig. 4. Reference heating curve with set supply temperatures over outdoor air temperatures. Supply temperatures T1 – T9 mark the simulation parameters for optimization.

To simulate the building heat demands, we used the minimum required data inputs described in section 2.2. The ground areas were taken from the dimensions of the graphical building representations in QGIS. Information about the number of floors and usage types of the buildings was available from facility management and site visits. Most of the buildings are used for research and contain office and laboratory spaces. With this information in the database, TEASER was used to model and simulate all buildings on campus. The heat demands were saved in hourly time-steps for the year 2013, for which on site measured weather data was available.

For the substation models, the buildings' heating systems were assume to be run with fixed supply temperatures of 70 °C and return temperatures of 55 °C. All pipes were assumed to be surrounded by a constant ambient temperature of 10 °C. The supply temperature was determined according to the heating curve shown in Fig. 4 as a result of the measured outdoor air temperature. With these assumptions, we used the automated network modeling approach described in section 2.4 to model and simulate the entire district energy system for the year 2013 with an hourly time-step.

3.1. Scenario 1: Supply temperature optimization

Scenario 1 illustrates the use of the presented approach to investigate a possible low-cost solution to increase primary energy efficiency in a district energy system. To define primary energy efficiency, a primary energy cost function for this case can be formulated as:

$$\min(C_{PE}) = Q_{gas} \cdot f_{PE,gas} + W_{el} \cdot f_{PE,el} \tag{1}$$

Since we are not trying to solve an optimization problem analytically, it is not necessary to explicitly formulate constraints with this cost function. Using heuristic optimization by evaluating the cost function based on simulation results, the constraints are implicitly part of the model we generated. As mentioned in section 2.4, freely available packages buildingsPy and ModelicaRes can be used to automatically simulate the model and analyze the results in Python. This allows us to implement a variation of a simple hill climb optimization algorithm [17] which simulates a population of models with varying simulation parameter values, evaluates the results and mutates the parameter values for further generations of candidate models, seeking to minimize the cost function given in (1).

As the focus of this optimization is on demonstration and proof of concept, rather than on efficiency of the optimization algorithm we mutate the variables in a simple form. For every simulation parameter of a newly initialized individual we mutate the parameter with a probability of 50 % or otherwise use the value from the previous generation. The population is divided into 50 % exploiters and 50 % explorers. The exploiters use the current best individual as their single parent for mutation by a normal distribution around the previous value in order to exploit the current local optimum. The explorers randomly chose mutated values within the minimum and maximum bounds in order to search the solution space for other local minima. For this optimization, we chose the supply temperature set-points marked in Fig. 4 as simulation parameters to be varied by the optimization algorithm.

This leads to an optimization problem with 1 objective function and 9 variables. We set the optimization algorithm to a population size of 11 individuals per generation with a runtime of 1 initial and 10 subsequent generations. For the optimization we use a computer with a 6 core/12 thread processor at 2.9 GHz with 32 GB of RAM. On this setup, the total runtime for the optimization requires approximately 3 days. As this optimization approach is a stochastic process, we perform 5 optimization runs and evaluate average, best case, and worst case results.

3.2. Scenario 2: Building envelope retrofits

In contrast to scenario 1, the retrofit of building envelopes in this scenario would require high investments and more time to implement. The building simulation process described in section 2.2 allows for a fast estimation of the energy savings potential of such measures. As input data of each building's floor area, usage type, number of floors and year of construction is available from the database as described in section 2.1, the reference scenario's building heat demands can be directly simulated.

In order to simulate the heat demands after retrofit, the only change necessary is the information about year of retrofit. Given a recent year of retrofit, TEASER will assume better insulated building envelope properties in the form of an additional insulation layer added to the existing representative wall construction. The width of the insulation layer is chosen such that the resulting U-Value of the wall in total will fulfill German energy saving ordinances in effect at the given year of retrofit. The resulting new heat demand tables from the updated simulation can be compared to the reference case directly as well as used in a heating network simulation of the entire retrofitted district. Thus, the energy savings potential can be estimated on building scale as well as on district scale, the latter of which also takes into account the effects of the retrofit on the district energy system. With the primary energy factors and heat generation efficiency, this can lead to an estimation of the primary energy savings.

As a result of the retrofit, we expect the lowered total heat demand in the district to cause effects on the district energy system's supply and distribution. Because less overall energy needs to be transferred in the pipe network, we expect pump energy to decrease. At the same time, unchanged pipe diameters and a lowered volume flow rate may lead to increased relative heat losses in the distribution system. Therefore, we analyze a combination of Scenario 2 with the heating curve optimization of Scenario 1, which we will denote Scenario 1+2. In this Scenario 1+2 we will investigate, how the resulting heating curve from optimization differs between Scenario 1 and a fully retrofitted district in Scenario 2.

4. Results

Fig. 5 gives an overview of the results from simulations and optimization runs for the reference case and the scenarios described above. In scenario 1, an optimization of the heating curve yielded a new heating curve, with which yearly primary energy demand in the model was reduced by 7.5 %. In comparison, the retrofitting of all building envelopes in the district energy system reduced primary energy demand of the central heat supply by 45.6 %. A combination of Scenario 2's building retrofit and a new heating curve optimized to that system setup reduced primary energy demand by another 7.9 % compared to the Scenario 2 result, so the model predicted an overall primary energy reduction by 49.5 % compared to the reference case (labeled Scenario 1+2 in Fig. 5).

In Scenario 1, the reduction of primary energy demand in the district energy system is the direct result of changing the heating curve control parameters determining the set supply temperature during operation. This is thus a very low-cost implementation with a significant primary energy reduction potential. As stated above, the optimization leading to this result was done in a stochastic process, which cannot guarantee to find a global optimal solution. The result shown in Fig. 5 is the best result achieved in 5 independent optimization runs. In the worst case optimization run, the optimization found a heating curve which reduced primary energy demand by only 1.5 %. On average, the optimization was able to find a 3.8 % improvement over the reference case.

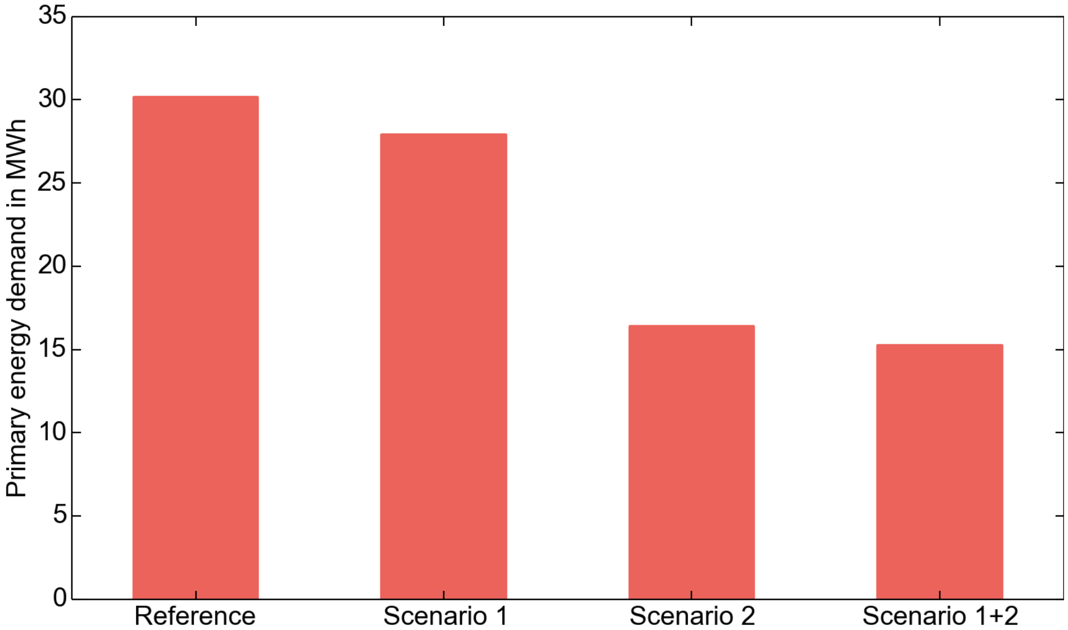

Fig. 5. Primary energy demands from simulation and optimization for the reference case, scenarios 1 and 2, and a combination of both scenarios.

For Scenario 2, the model predicts a large reduction of primary energy demand. Yet, these reductions would require large investments in building retrofits and this would take significantly more time than the control parameter changes in Scenario 1. Nevertheless, it is also an interesting scenario to consider from a district energy system perspective. The reduction in building heat demand itself does not require a district energy system simulation, but can be achieved with simulations of the building stock heat demand. In our example, the automated building simulation tools can be used to determine the heat demand reduction at building level. This resulted in an overall heat demand reduction of 49.7 % over the whole district. Yet, overall primary energy reduction at the heating plant was only 45.6 %. In this case, the model predicts that some of the benefits from building retrofit would be countered by higher relative heat losses in the network if plant operation would not be adjusted to the new heat demands. Thus, the scenario illustrates how a holistic system model can deliver additional information about system behaviour in an integrated context.

When combining the lower building heat demands from Scenario 2 with the optimization routine from Scenario1to find a heating curve that is better suited to the new demand side behaviour, overall primary energy demand at the heating plant could be reduced by 49.5 %. This still does not fully realize the reduction potential from the building heat demands of 49.7 %. Again, this is the best heating curve result from 5 optimization runs. It is possible that another optimization run, optionally with improved optimization settings, would yield an even larger improvement. Also, it would be interesting to further investigate the new operation of the distribution network, as it is likely that with such a large reduction in building heat demands, the pipe network will be over-dimensioned.

5. Conclusions

In this paper, we present an integrated approach for investigating the effects of different scenarios in district energy systems based on a dynamic system model and illustrate its application with two scenarios for a university campus. We were able to reduce the manual effort for modeling and simulating a reference version and variants for different scenarios with automation of processes based on a GIS representation of the campus, component models in Modelica and supportive software tools in Python. The example results showed that the presented approach is suited to evaluate different scenarios for reducing primary energy demand of a district energy system, ranging from improved operation to changes in system design, and a combination of both.

Nevertheless, the approach and especially the results presented in this paper should be regarded as a proof of concept rather than a definitive solution to district energy system optimization. Further work on this topic should include improvements on model performance and validation as well as on the optimization process. The individual component models for the network and supply modeling are still relatively limited and have to be validated against measurement data to ensure that they can accurately predict the dynamic behavior of the real system. Furthermore, the comparably long simulation run times require efficient settings for the optimization algorithms. We expect that improved optimization procedures can significantly improve speed and result quality of such system optimizations.

In addition, we aim at further improvements to the presented approach that will enable the combined investigation of energy flows in a city district including heating, cooling and electricity. For a wide applicability of the presented tools, we plan to open up development with open source releases in the near future. This process has already started with the release of the Modelica model library AixLib and will continue with the building modeling tool TEASER.

Acknowledgments

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Nomenclature

Letter Symbols:

C primary energy cost function, kWh

F primary energy factor, -

Q heat input, kWh

W electric pump work, kWh

Greek symbols

η efficiency

Subscripts and superscripts

el electricity

gas natural gas

PE primary energy

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