Using Evolutionary Algorithms to Design Energy Supply Systems for a Changing Building Stock

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Abstract

Central energy supply units for district heating grids need to be planned for a relatively long usage due to large investments. During this long usage period, building retrofits may change the demand patterns of the building stock. These changes might have an effect on the used energy supply units. As static tools do not adequately address this, we propose to use dynamic building simulation for individual buildings to determine the future heat demand. In order to find good solutions for a retrofit order of the buildings and design of energy supply systems that meet the given technical requirements two individual optimizations are performed, both using evolutionary algorithms (EA). The methodology is applied to a research campus with over 200 buildings.

Introduction

The focus for energy supply of buildings shifts from single buildings to the integral consideration of multiple buildings on urban-scale. Large building stocks are constantly changing, buildings are demolished, retrofitted or new-built. These developments lead to a changing demand and influence the dynamic heat load of building stocks. Changes on the demand side influence the energy supply system, in particular of those systems where multiple buildings are connected to a local heating network with a central feed-in. Current design strategies for energy supply systems of multiple buildings are often based on static, yearly heat demand values. This does not consider two important effects. The long term effect of a changing building stock and its demand and the short term effect of dynamic behavior of energy supply systems. Thus the question arises, whether dynamic building simulation, in combination with evolutionary algorithms (EA) can improve the design of central energy supply systems on urban scale. This paper presents a two-step approach to evaluate a) a suitable retrofit strategy for multiple buildings for a given period of time (15 years) and b) an energy supply system with central feed-in to satisfy a building stocks changing future heat demand.

To consider interactions between buildings and energy supply systems, one key element is the dynamic heat demand profile of buildings. To calculate dynamic heat demand profiles, Building Performance Simulation (BPS) is a widely used method. On urban-scale, several approaches are available. There are already existing tools dedicated to urban-scale BPS like CitySim (Robinson et al. (2009), Kämpf and Robinson (2007), Kämpf and Robinson (2009)), which uses a dynamic thermal model. Another possibility is to define archetype buildings, use single building simulation software and aggregate the results for whole cities. Examples can be found in Mastrucci et al. (2014) and Cerezo et al. (2015). One drawback of these approaches is the lack of individual profiles for multiple buildings.

The design of central energy supply systems is mainly dominated by conventional design methods, based on suggestions for a good energy supply design. These design methods mainly refer to values like full load hours and number of starts to evaluate the suitability for the use case. Nevertheless, Schaumann (2010) points out that CHP design is overall a complex work with a lot of different factors like energetic, economic or ecologic factors needed to taken into account. The major uncertainty still is the future demand, which is not predictable but can be approximated by different scenarios.

Evolutionary algorithms, in particular genetic algorithms (EA, GA) are already widely used in simulation-based optimization for building design, retrofit strategies and for design and control of energy supply systems. On single building scale EA are often used to determine design parameters in early design stage. Tuhus-Dubrow and Krarti (2010) investigated the building's shape, window-to-wall ratio, physical wall and window properties. Wang et al. (2005) used similar design variables. In addition to architectural design parameters, Kämpf et al. (2010) compared set temperatures for heating and cooling systems. Widely used tools on single building simulation-based optimization include GenOpt (Wetter et al. (2001)), Mobo (Palonen et al. (2013)) for GA and EnergyPlus (Crawley et al. (2001))

and IDA-ICE (Björsell et al. (1999)) for BPS. For multiple buildings Kayo et al. (2016) investigated the number and power of Combined Heat and Power (CHP) units for four campus buildings. The energy demand was provided by measurement data. Kämpf and Robinson (2009) applied a GA in combination with CitySIM to find optimal retrofit strategies for a district in Basel, Switzerland. A comprehensive literature review on optimization methods, including GA, in combination with BPS can be found in Nguyen et al. (2014), a review on computational optimization for sustainable building design is given in Evins (2013).

This paper presents a methodology for the design of energy systems to supply multiple buildings connected to a district heating network using multi-objective evolutionary algorithms. The objective functions are to minimize primary energy use and life-cycle costs. The methodology takes a changing dynamic heat demand of the building stock due to retrofit measures into account. To evaluate different retrofit scenarios, a first optimization determines the order in which buildings could be retrofitted. The optimization of the energy supply system is evaluated using one exemplary result of the first optimization and considers then several technical requirements (minimal part load ratio, maximum flow temperature, minimum consecutive operation hours).

Methodology

Urban Scale Building Simulation

The first step of the presented methodology is the determination of space heating demand of the investigated building stock. One option is to use monitoring data of the buildings. However, high-resolution monitoring data is not always available. In addition measured data needs data driven models to determine future heat demand. Another option is to use design-driven BPS to calculate current and future heat demand.

Dynamic building simulation models for urban energy modeling require a good trade-off between accuracy and computational effort. Addressing this needs, we use a Reduced Order Model (ROM) from Modelica libary AixLib, available open-source at https://github.com/RWTH-EBC/AixLib. The Reduced Order Model in AixLib is explicitly developed to model and simulate multiple buildings on urban scale (Lauster et al. (2014)). The ROM is based on the German Guideline VDI 6007-1 (German Association of Engineers (2012)) and has been verified with the VDI 6007 test cases as well as ASHRE 140 (Lauster, Brüntjen, Leppmann, Fuchs, Teichmann, Streblow, and Müller (2014), Lauster, Remmen, Fuchs, Teichmann, Streblow, and Müller (2014), Lauster et al. (2016)). In addition to the ROM for thermal behavior of different zones, we are using a model to simulate heat consumption conducted of a central Air Handling Unit (AHU), which is also capable of describing heat demand for de- and humidification (Mehrfeld et al. (2016)). Various applications already showed the applicability and use of the model in the urban-scale context (Schiefelbein et al. (2015), Fuchs et al. (2016))

To use a design-driven BPS model, like the above mentioned, and to predict future heat demand considering retrofit measures, it is necessary to provide a full-scale parameterization for each building. This includes the architectural design, usage and interior layout as well as building physics properties (like wall constructions). However, on multiple building and urban scale the level of detail of building information is often low or no informations are available at all. To generate individual building models for all investigated buildings we are using the enrichment, parameterization and workflow-automation tool TEASER, available open-source at https://github.com/RWTH-EBC/TEASER. TEASER reduces the amount of necessary building information to five basic parameters, such as building usage, year of construction, net floor area, height of building and number of storeys above ground. The structure and methodology of TEASER is described in more detail in Remmen et al. (2017). TEASER uses these five parameters in combination with statistical and normative data to generate a full-scale parameter set for every building. The usage of the building determines the interior layout, splitting the building into different usage zones with similar thermal conditions, according to Lichtmeß (2010). Internal gains from Deutsches Institut für Normung (2011) (German Standard for energy calculation of buildings) with additional data for hourly profiles from SIA 2024 Swiss Society of Engineers and Architects (2006) (Swiss data sheet) are attached to each usage zone. Given the net floor area, height of the building and number of storeys above ground TEASER calculates the total wall and window area facing the ambient according to BMVBS (2010) (German study for geometrical and technical data assumption of buildings). The total wall and window area is distributed linearly to each thermal zone. From the given year of construction typical wall constructions (number, thickness and material of layer) and windows are chosen and assigned to the building (Loga et al. (2005)). This results in a fully described building parameter set that can automatically be exported to models of Modelica library AixLib. The gained building simulation model is based on enriched data to achieve a simple and efficient way to simulate buildings on urban scale, thus the models combine statistical and individual information.

TEASER provides different functions to apply simplified retrofit measures on the building to estimate the heat demand after such retrofit. To insulate exterior walls including rooftops and ground floors, an additional insulation layer with a thickness to German regulation for energy savings in buildings is attached to the walls (EnEv (2014)). Another possibility is to exchange windows with improved glazing that also meet the same energy saving requirements. A third option is a combination of both retrofit actions. Costs for all three retrofit measures are taken from BBSR (2014), which is a report for retrofit costs on German non-residential buildings. It is worthwhile mentioning that only costs that are purely related to energetic retrofit of exterior building elements are considered in this work. Capital investments not made after the first year are discounted with a variable internal rate of return.

In this case, the reduction of the operational costs due to energy savings are not considered in the net present value of the building retrofit, but taken into account in the net present value calculation of the energy supply system. Here, the net present value or capital investment costs of the retrofit is taken into account as a initial investment, leading to a consideration of the reduced energy demand of the buildings and therefore reduced operational costs of the buildings. With this the net present value of the energy supply system represents the net present value of the combination of retrofitting buildings and installing a new supply system.

Energy Supply Calculation

The goal of the presented methodology is to design a centralized energy supply system for a district heating network to minimize primary energy and maximize the net present value (NPV). Both primary energy and NPV are dependent on fuel consumption of the system, thus on operation time and mode (e.g. full-load or part-load). To determine the fuel consumption we implemented calculations for Combined Heat and Power (CHP) as well as for boiler systems. For CHP we also consider the electrical output, which can be fed in to the public transmission grid or used by the buildings on the campus itself.

The energy supply calculation uses dynamic heat demand profiles for all buildings from the first optimization for an investigated period as the calculation basis. Furthermore the number of CHP units and their thermal power needs to be specified. Regarding the thermal power, we are using regressions with data taken from ASUE (2015a), ASUE (2015b), Schaumann (2010) to calculate all other necessary parameters for motor and gas turbine CHPs (electrical power, thermal efficiency, electrical efficiency, lower part-load ratio initial and operational costs). In addition motor CHPs have a prescribed flow temperature of 90 °C whereas turbine CHPs can provide higher flow temperatures. The required flow temperature of the district heating network is provided by a linear function dependent on the ambient air temperature. We assign a minimum operation time to each CHP, which can be variable. This prevents the CHP to switch too often between on and off operation mode as this is a technical constraint. The CHP units may operate in part-load with the constraint of not falling below the lower part-load ratio. The part-load efficiency is considered to be constant, which is compliant with the given data sources.

One boiler is assigned to every proposed system. To determine the technical configuration of the boiler, we first consider the thermal power to be infinite. The boiler has two operation modes. The first mode is if the CHP units are not able to satisfy the heat demand of the buildings. This might be the case for heat demand below the lower part-load ratio of the CHPs or for very high heat demand where the boiler serves as a peak load supply. The second mode is if the chosen motor CHP units are not able to provide the required flow temperature of the network ($T_{flow} > 90$ °C). With the knowledge of the boiler operation, the thermal power of the boiler can be set. Boiler characteristics (efficiency, costs) are calculated with parameters from a regression taken from Scheunemann and Becker (2004) using the thermal power of a boiler.

The output of the energy supply calculation is the gas consumption of the energy supply set up and the potentially produced electricity for each hourly time step for the given period. To calculate life cycle cost, the gas consumption is considered with a gas price of 2.65 ct/kWh (Statistisches Bundesamt (2016)) over the considered system lifetime. With use of measured data for the used electricity of the obtained buildings it is evaluated if the potentially produced electricity can be used directly within the buildings or is fed into the public power grid. Both, own usage and feed-in, result in a credit for the specific energy supply combination in the life cycle costs, where the pricing is taken from the German CHP law (Bundestag (2002)). We assume a constant price for electricity at 12.86 ct/kWh as given by Statistisches Bundesamt (2016) for 2016.

Evolutionary Algorithm Optimization

Optimization methods based on evolutionary algorithms or in special genetic algorithms are using the process of natural selection theorized by Darwin, to evaluate and find the best so-called individual for a particular problem. It was introduced by Holland in 1975 and is now used in a large range of different types of optimizations and building optimization problems (Evins (2013)).

This section gives a short introduction into GA, where we concentrate on genetic algorithms within the EA. Every GA starts with a defined number of *individuals* with a certain *fitness function*, which describes the actual optimization problem and evaluates every individual. All individuals gathered are called *popu-*

lation. Every evaluation of a new population is called *generation*, between two generations the population may breed through *crossover* and *mutation* similar to processes in nature. Whereas mutation stands for a random change of the genes (properties) of the individual and the crossover stands for the inheritance of certain genes of two individuals to one resulting new individual. In the presented work we use the ordered crossover method described in Goldberg (2012) and the Shuffle Indexes Method for the mutation according to Félix-Antoine Fortin et al. (2012).

The optimization problems can be defined as single-objective or multi-objective optimization problems, whereas single-object problems leads to one very best, optimal solution (local or global). Multi-objective problems on the other hand are dependent on two or more problems, often related with a negative correlation. For example the maximizing of the primary energy saving while minimizing the costs, in case of a building retrofit. Multi-objective optimization problems are resulting in a Pareto set, showing all individuals not dominated by another individual. Every individual in this Pareto set is a optimal solution for the certain combination of the two objectives.

Genetic algorithms in general are meta-heuristic algorithms, not assuring to find the global optimum. This is, compared to traditional, global optimization algorithms one of the major disadvantages. On the other hand GA can deal, according to Yang (2010), with complex optimization problems, where for example the objective function could be stationary or non-stationary. One popular genetic algorithm according to Evins (2013) and Basurra and Jankovic (2016) is the NSGA-II (Deb et al. (2002)) algorithm. It is characterized by a high computational efficiency and good performance. This algorithm looks for a good trade-off within the solution space, while treating all objectives as being equally important (Basurra and Jankovic (2016)).

Software Framework and Workflow

To connect BPS, energy supply calculation and GA we are using a Python software framework, consisting of different Python packages and modules. To manage information of multiple buildings and energy supply systems in Python we are using a package called PyCity developed for handling energy related data on urban-scale context (Müller et al. (2016)). This package is able to handle the geographical positions of the buildings and energy supplies and at the same time manage semantic data as well as time series. An open-source release of PyCity is planned for the future. In a first step all available semantic information about the building stock is read in PyCity. The minimum information for each individual building, described above, is passed over to TEASER. TEASER is used to generate four different ready-to-run simulation models for every building (status quo, retrofit walls, replace windows, retrofit walls and replace windows). These models are simulated using Dymola 2017. The received results for all buildings are stored in PyCity. In addition, PyCity can manage an arbitrary number of supply units. These supply units hold also semantical information (like power and efficiency) as well as exact time series of their thermal and electrical output and fuel consumption. After initializing all necessary information within PyCity, the actual process of the genetic algorithm can be applied. We are using the Python package deap (Félix-Antoine Fortin et al. (2012)), which allows to set up individual toolboxes and offers a variety of different multi-objective genetic algorithms.

Figure 1 shows the schematic workflow of the methodology. In a first optimization, the order of retrofit measures is evaluated, resulting in a Pareto set of possible solutions. The user takes one of these solutions (e.g. cost-optimal or energy-saving-optimal or something in between) and passes it to the second optimization for energy supplies. The energy supply calculation uses the dynamic energy demand profiles for the given period (e.g. 15 years) and computes a second Pareto set with solutions for optimal energy supplies, for the given retrofit scenario.

Use Case - Research Campus

The methodology shown in the last section is applied to a real-world use case. This section starts with an overview of the investigated research campus. Followed by a description of the used parameters and boundary conditions for the two step optimization a) building retrofit scenarios and b) energy supply design.

Research Campus Jülich

The subject of our use case is the research center Jülich in Germany. The research campus consists of over 200 building with different usage, for example offices and laboratories. The building stock consists of buildings from various construction periods, with a peak between the year 1958 and 1968. Nearly all buildings on the research center are connected to a district heating network, which is supplied by waste heat of a nearby lignite-fired power plant. The research center is willing to investigate different future scenarios with a new energy supply system. Considering the existing infrastructure for district heating, the new concept could be a centralized solution. To reflect different future scenarios, one possibility is to apply a retrofit scenario to the research center and calculate different possibilities for the energy supply system based on an optimization. Both, retrofit measures as well as the energy supply system are restricted by constraints. These constraints, as well as boundary conditions and the workflow will be discussed in the following subsections.

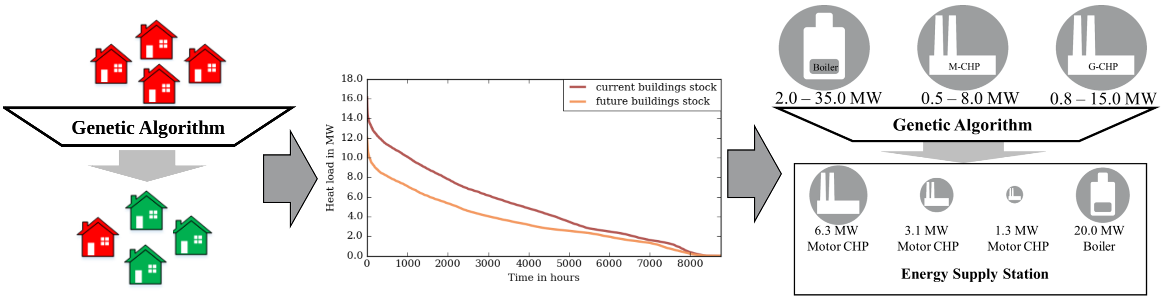

Figure 1: Process of 2-step Algorithm

Building Retrofit Scenarios

The first step is the optimization of the retrofit order of the buildings. There are two reasons for applying such a retrofit order optimization. On the one hand this tool can assists the facility management of the research center to evaluate their own retrofit plans, on the other hand we are getting multiple solutions that can be used for further investigations. As mentioned before, simulated yearly heat demand load curves, using measured weather data from the research center for the simulation, for all four building options are stored in PyCity. We are using the NSGA-II algorithm to solve the multi-objective problem of maximizing the energy savings due to the retrofit and maximizing the net present value of the retrofit measurements. The used algorithm setup is listed in Table 1. To solve the optimization problem, the algorithm creates a set of indexes describing a retrofit measure of one building with each index. This leads to a certain order of building retrofits. This retrofit order is considered as one individual in our optimization, whereas every retrofit measure within this list can be imagined as a gene. The used crossover probability is 80 %, which means that 80 % of the individuals in one generation are used for an ordered crossover. The ordered crossover leads to new individuals by reusing and reordering certain genes of two individuals selected for this crossover. In our case the algorithm reorders the lists of retrofit measurements with the ordered crossover method and with that takes the crossover of the Genetic Algorithm into account. The used mutation rate of 20 % describes the probability that an individual is chosen for a mutation pool. All individuals in this mutation pool have then a mutation probability of 5 % to actually mutate and randomly reorder the list of retrofit measures. Further investigation on crossover and mutation rate in the context of building optimization with genetic algorithms can be found in Alajmi and Wright (2014).
The order of retrofit measures underlies some technical constraints. First, the duration of the retrofit scenario needs to be specified. In our case we consider the next 15 years. Assuming limited funds for yearly investments in retrofits, a second input boundary is a certain renovation rate. The renovation rate describes the retrofitted area per year in relation to the cumulated area of all buildings. The renovation rate in this scenario is set to 3.26%. To discount investments that are not made in the first year, we set the discount internal rate of return to 4%. Due to a uncertain future of the current energy supply system, it is hard to assume an energy price for heat, thus we are not considering cost savings due to the energy saving of the retrofit. As an output we are getting all buildings that are retrofitted in the given period with the exact knowledge of the time of retrofit (year) and the type of retrofit.

Energy Supply Design

The second step is the energy supply design optimization. For that, we pick one solution of the Pareto set of the retrofit scenario optimization, to account for a changing heat demand in the future. Again we are using the NSGA-II algorithm to solve the multi-objective problem of minimizing the primary energy and at the same time maximizing the net present value, using the calculation method described in the previous section. Algorithm parameters can be obtained from Table 1. Like in the building retrofit algorithm we use a list, representing one individual. The entries in this list could be imagined as genes and the order of this list indicates the order of the CHP units used to provide the thermal demand. Each entry in this list stands for a CHP unit, the type of the CHP unit and the power of the CHP unit. Currently, the algorithm is restricted to work only with a fixed number of supplies. For our use case, we chose to investigate 3, 5 and 8 CHP units. Due to the base load of the heat demand of 2 MW and a peak load of 18 MW, the modularity of choosing more CHP units then one might be interesting. For this work we also set limits to the maximum thermal power a CHP or boiler might have. The values used in this work for thermal power range, the costs per unit and the maximum forward-flow temperature are shown in Table 2. The required supply temperature is controlled by a heating curve. Based on the current outdoor air temperature, the heating curve calculates a set supply temperature for feed-in to the network between 95°C to 120°C. It is obvious

Table 1: Used algorithm setup for step one and step two

Algorithm parameters	Building retrofit scenario	Energy supply design
Nr. of individuals	2000	200
Generations	10000	200
Mutation rate	0.2	0.2
Crossover probability	0.8	0.8

Table 2: Used properties for the different energy supply units

	Motor-CHPs	Turbine-CHPs	Boilers
Thermal Power Range	0.5 - 8.0 MW	0.8 - 15.0 MW	2.0 - 35.0 MW
Cost Range per Unit	0.592 - 5.918 Mio.€	0.303 - 3.824 Mio.€	0.042 - 2.305 Mio.€
Maximum Forward Temperature	$< 90°C$	$> 140°C$	$> 140°C$

that motor CHP units always need an auxiliary boiler to maintain the required flow temperature. The minimum runtime for CHP units is set to 8 hours.

Results

This section presents the results of applying the developed two-step optimization process to the use case described above. Figure 2 shows the resulting Pareto set of the genetic algorithm finding a retrofit order. Each dot on the set describes a certain retrofit

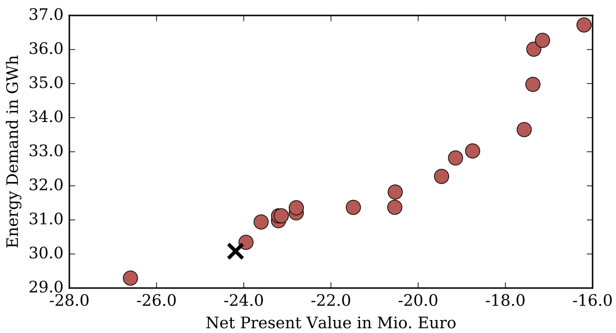

Figure 2: Pareto Set of the GA with a retrofit rate of 3.26% (marked cross describes the chosen result for step two)

order and the associated retrofit measures. The lower left bound represents a retrofit strategy with a high energy saving potential, leading to a low energy demand in the future with the side effect of high costs and therefore a low net present value. The upper right bound represents the best found solution for a high net present value but a lower amount of energy saving after the investigated period of 15 years. Nevertheless each point on the Pareto set describes a non dominated solution which means that there was no better retrofit strategy found compared to one of the optimization functions.

To start the second step of the methodology, the energy supply design, we are choosing one optimal solution on the Pareto set with a net present value of -24.188 Mio. Euro and an energy demand of 30.080 GWh (marked as a cross). This point is chosen because it is the retrofit strategy, achieving high energy saving, while being not to far aside of the other solutions. This certain retrofit strategy contains for example a retrofit of 5 buildings in the first year, where 2 of them are fully retrofitted, 2 are wall insulated and one building receives a window replacement. This retrofit strategy is used as a basis for the future heat demand and the following energy supply optimizations are based on that retrofit strategy.

Figure 3 shows the Pareto set of the results of

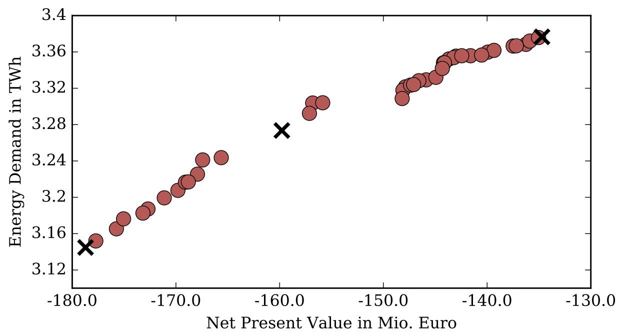

Figure 3: Pareto Set of the GA with 3 Supplies

the energy supply optimization with the calculated primary energy use and the net present value achieved after the duration. The principle is the same as in the Pareto set in Figure 2, with the main difference in the actual values of the axes. The net present value is calculated with all costs and savings during the 15 years. As we chose to not compare the solutions to the current energy supply system we can't achieve positive net present values due to the fact that we have costs at any time of the investigated period. The lower left bound, marked with black crosses, shows the result with 3 CHP units with the lowest energy use. The upper right corner is the solution with the best net present value found, but leading to a high primary energy use. For a better interpretation of the results Figure 4 shows the Pareto set of the GA with 8 Supplies. A comparison of the two curves shows that the total primary energy use is not really effected of using 5 more supply units. The net present value on the other hand is consistently higher due to the higher investment costs of more CHP units. To show the

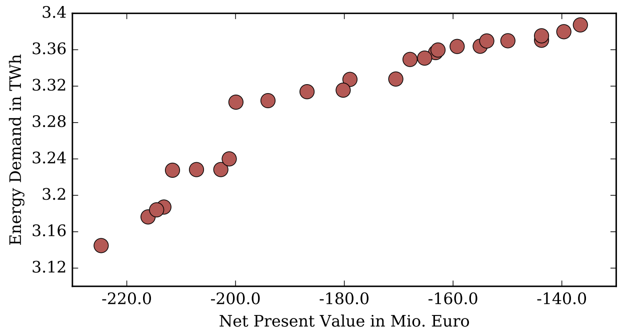

Figure 4: Pareto Set of the GA with 8 Supplies

capability of the GA, we now want to exemplarily present three optimal results of the Pareto set with three CHP units found. Therefore we use the three marked crosses from Figure 3. Starting with the point on the upper right with a net present value of -134.71 Mio. Euro and a total primary energy use of 3.38 TWh. This cross contains 3 motor driven CHP units with a thermal power of 6.8 MW, 3.05 MW and 1.3 MW. This solution is also shown in Figure 5 with the two annual load curves, one representing the actual building stock and one representing the future building stock after the retrofitting measures within the next 15 years. Due to the higher costs

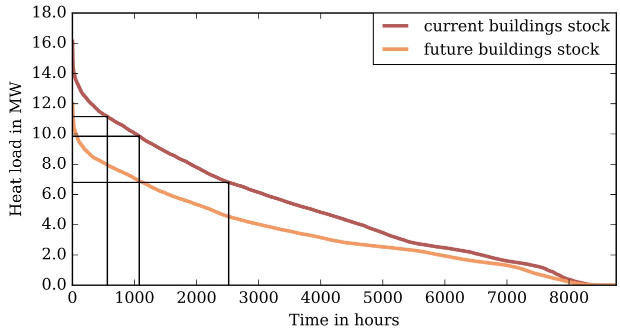

Figure 5: Annual Duration Curves with a exemplary solution on the Pareto set

of turbine CHPs it is expected that there are no turbine CHP units in the best net present value result. Inspecting the point at the lower left end of Figure 3, we see that this energy supply system leads to a net present value of -178.72 Mio. Euro and a total primary energy use of 3.14 TWh. This individual has 3 turbine CHP units with a thermal power of 14.8 MW each. The primary energy use could be explained by the fact, that the forward flow after the CHP units does not needed to be reheated before supplying the buildings, this has to be done when using motor CHP units. The low net present value could be explained by the large supply units with a high investment. The middle point, marked as a black cross in Figure 3 describes an energy supply system with a primary energy use in the middle of the primary energy use of all good solutions. This point describes an energy system with again 3 turbine CHP units with a thermal power of 9.8 MW, 11.8 MW and 11.8 MW, leading to a net present value of -159.79 Mio Euro and a total primary energy use of 3.27 TWh.

To discuss the capability of the energy supply design algorithm we now compare the results to a boiler only scenario and one traditional design CHP unit. The boiler-only scenario contains one large boiler, capable of supplying the needed thermal demand for the whole district. The traditional design CHP unit is chosen according to the annual load curve of the actual building stock by finding the thermal power for a CHP unit with a minimum full load hours of 5000. This leads to a thermal power of 3.3 MW, either motor or turbine. For the presented result in Figure 6, the 3.3 MW CHP unit is investigated as a motor driven CHP unit, leading to a better net present value and primary energy use as the same thermal power turbine CHP. The compared GA

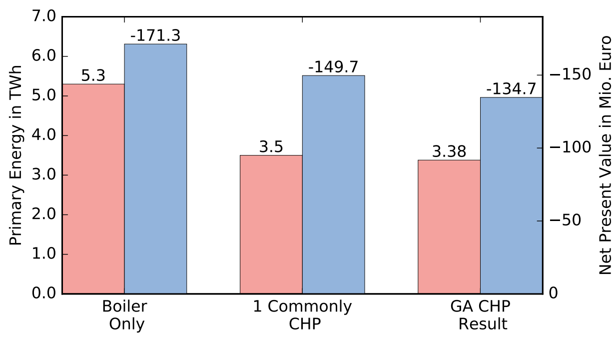

Figure 6: Comparison of the exemplary chosen Energy Supply Design with a boiler and a 5000h full load hours designed CHP unit

result is the best net present value result of Figure 3. In comparison, the boiler-only scenario is the cost intensive scenario with a net present value of -173.3 Mio. Euro and a total primary energy use of 5.3 TWh. Followed by the traditional design CHP unit with -149.7 Mio. Euro, where the GA result is in this comparison the best result, regarding both the primary energy use as well as the net present value with -134.7 Mio. Euro. To conclude this comparison, the GA achieved, a lower primary energy use as the two compared scenarios, even with the highest primary energy use result.

Limitations And Future Research Work

The presented methodology has some known limitations, which also lead to future research work. Regarding the optimization, one main disadvantage of using multi-objective GA is the uncertainty to find only local optima. On the other hand, the easy-to-use toolbox of deap and the possibility of implementing arbitrary simulation models into the process is considered to be an advantage. Furthermore a coupled optimization of the retrofit order of buildings and the design of energy supply system may deliver different results. However, for the research campus both actions are necessary and carried out in any event. In the current version of the methodology the energy supply calculation neither considers the dynamics of the network nor offers the possibility to add storages or include trigeneration for a possible link to the district cooling network. It is planned to move the calculation for the energy supply to Modelica, using the FastHVAC library (Stinner et al. (2015)) and couple it with dynamic network models (Fuchs et al. (2016)). One major challenge to tackle is the expected high computational time. The consideration of retrofit actions and especially the triggered costs of retrofit need to be reviewed and enriched with additional data. This also applies for energy supply units. The results have not been subject of sensitivity analysis, regarding changing weather influences in the future, prices for gas, electricity and costs for retrofit. Although the methodology was applied to a research center in Germany, a heating dominated region, the building model itself is capable to determine the cooling demand and could be applied to a cooling dominated region.

Conclusion

Static or yearly values are often used to design centralized energy supply systems connected to a district heating network. In addition the changing building stock due to retrofit measures or demolished and new buildings is usually not considered in the design of those systems. In this paper we combine individual Building Performance Simulation for multiple buildings on urban scale with the design of centralized energy supply systems. The presented approach uses two multi-objective genetic algorithm optimizations to determine a) the order of retrofit actions of the buildings and b) the design of a centralized supply system. Using TEASER, a workflow automation tool for BPS on urban-scale, we generate individual simulation models in four different conditions (status-quo, retrofit walls, replace windows, retrofit walls + replace windows) for each building using the Modelica library AixLib. By assigning costs to the retrofit measures a first optimization identifies retrofit scenarios for the next 15 years, maximizing net present value and maximizing energy savings. One arbitrary retrofit scenario is picked and passed to the second GA optimization to design the the energy supply systems for the buildings. The algorithm can chose between different CHP technologies (motor and turbine) and its objective is to maximize the net present value and minimize the primary energy use.
We applied the methodology to a research campus in Germany with over 200 buildings. We tested different GA setups with 3, 5 and 8 CHP units used for the supply of the research center. The results show that a wide range of possible optimal solutions where found. Comparing these results to common design methods such as a minimum full load time of 5000 hours for CHP units or the supply of one gas boiler supplying the district shows the capability of the algorithm finding optimal solutions. Nevertheless the presented optimization method has limitations such as finding only local optima or calculating with a constant energy price over the years. Thus the presented work showed a methodology to design energy supply systems for district scale and applied it successfully to a use case in Germany.

Acknowledgments

Grateful acknowledgement is made for financial support by BMWi (German Federal Ministry of Economic Affairs and Energy), promotional references 03ET1352A.

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