OPTIMAL DESIGN OF ENERGY SYSTEMS IN RESIDENTIAL DISTRICTS WITH INTERCONNECTED LOCAL HEATING AND ELECTRICAL NETWORKS

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ABSTRACT

This work introduces an approach to optimally design energy systems based on economic criteria for individual residential buildings and districts comprising microgrids (MG) and local heating networks (LHN). Further, the impact of different time series aggregation methods applied to input data for the design optimization is analysed.

The results show that an aggregation based on 7 typical 3-days periods with an intra-day temporal resolution of 1 h achieves in average 94 % shorter solving times than 12 typical days with 15 min resolution, while the accuracy is kept at ±0.96 % based on unaggregated references. Further, in a use case comprising 6 buildings the installation of combined heat and power (CHP) and heat pumps (HP) in a complementary MG and LHN enable cost savings up to 10.3 % compared to conventional heat and electricity supply.

Keywords: Optimal design, time series aggregation, typical period, MIP, distributed energy systems

INTRODUCTION

The design of distributed energy systems on a residential building or district level is a computationally complex task. It comprises the optimal selection and sizing of components, while maintaining optimal operation according to economic or ecological criteria. This task can be approached by using different mathematical optimization methods.

Weber and Shah (2011) optimized the design of the energy system of a town comprising residential and office buildings applying a mixed integer linear programming (MIP) approach. Technologies such as wind power, CHP, PV, heat pumps and solar thermal collectors are considered in a local heating network to satisfy heating, domestic hot water, cooling and electricity demands. Haikarainen *et al.* (2013) introduced a MIP for optimally positioning CHP units and small HPs in a local heating network that supplies 25 buildings. Mehleri *et al.* (2013) developed a MIP model that considers a LHN as well as a microgrid connecting five residential buildings. Electricity and heat demands can be covered by boilers, CHP, PV and thermal storages while total annual costs are being minimized. Stojiljković *et al.* (2014) introduced a metaheuristic for multi-objective optimization problem, where a trigeneration plant is designed while minimizing total annual costs and primary energy consumption. Evins and Orehounig (2014) optimized the components selection and sizing of an energy centre as well as the operation by introducing a bi-level optimization method. It combines a multi-objective genetic algorithm for design optimization and mixed integer linear programming (MIP) for operational optimization. Further, Veeramsetty (2014) used a particle swarm optimization (PSO) technique for the optimal location and sizing of distributed generation in a distribution network.

Based on a previous approach by Harb *et al.* (2014) and Harb *et al.* (2015), this work presents a MIP model that allows PVs, batteries, boilers, CHPs and HPs to synergize in a combined LHN and MG. The design and operation of a whole neighbourhood's energy system is optimized in subject to the demand of heating, domestic hot water and electricity. This leads to a large number of variables that can be handled by MIP. To reduce solving times, an improved time series aggregation method is investigated by quantifying relative solving times and deviations of the optimal objective values based on unaggregated reference optimizations.

Time Series Aggregation

The computing effort for solving optimization problems by MIP strongly depends on the number of time steps considered to represent the operation along the observation period. The intra-day temporal resolution is one parameter that affects the total number of time steps to be calculated.

Aggregation methods enable representing a certain time series by few typical periods that preserve the relevant demand characteristics and trends. Mehleri *et al.* (2013) introduced 3 typical days with hourly resolution for summer, winter and mid-season. The mid-season profile is averaged from April and November, the summer profile from July and the winter from February. Zhou *et al.* (2013) applied an approach with 12 typical days, which represent average profiles of each month. Domínguez-Muñoz *et al.* (2011) proposed a partitional clustering methodology. Based on quantified dissimilarities[1] all days of one year are arranged into groups of similar

[1] The dissimilarity between two days is defined by the Minkowski distance.

days by minimizing the sum of dissimilarities between the chosen typical day and the other days in each group. Fazlollahi *et al.* (2014) further developed this methodology in order to optimize the number of typical days. They also introduced an asymmetric segmentation of the typical periods for a further reduction of solving times. In contrast Cardoso *et al.* (2013) used a one-week profile with a temporal resolution of 15 min to describe the operation of a battery storage system in a MG.

The typical days methodologies greatly reduce the number of time steps considered within the optimization. The variations in demands and other parameters during one day are taken into account. Further, by defining different typical days, seasonal variations are considered as well. However, typical-days aggregations do not allow for considering inter-days energy shifts. Therefore, variations in demand and supply over a few days, which could be compensated by storage operation, are neglected. However, this effect can be considered by a multi-days aggregation as proposed by Domínguez-Muñoz *et al.* (2011) and Cardoso *et al.* (2013).

In this work, an alternative approach is investigated with the aim to minimize the solving times while maintaining high accuracy of the optimal solution. The accuracy and relative solving time savings are determined based on reference optimizations in which all 365 days of one year are simulated with a 15 min resolution i.e. 35,040 time steps.

Approach

We propose an algorithm that allows for aggregating the original time series into typical weeks as well as other period lengths, e.g. typical 3-days profiles. This algorithm is part of the pre-processing of the input data for the MIP optimization. The illustration in Figure 1 and the following explanations apply to a weekly aggregation. This methodology is analogue for different period lengths. We assume that the original data is a time series of 365 days with an intra-day temporal resolution of 15 min. The user must set the desired resolution Δt in minutes, period length T_{period} in days and number of typical periods N_g. First, the number of days per year is reduced to the largest smaller integer multiple of the period length. Since one year consists of 52 weeks plus one day, the last day, respectively the last 96 entries are cut off. Subsequently, an hourly, half-hourly or quarter-hourly averaging is performed to reduce the temporal resolution. The periods (weeks) are then allocated to N_g different groups, from which the typical profiles will be derived. In this case, the reduced time series is subdivided into 7-days periods. For the allocation, the values of each week are summed over the whole period, i.e. the weekly sums are determined. The range between the smallest and the largest weekly sum is divided into N_g sub-ranges, which represent N_g different groups of aggregated

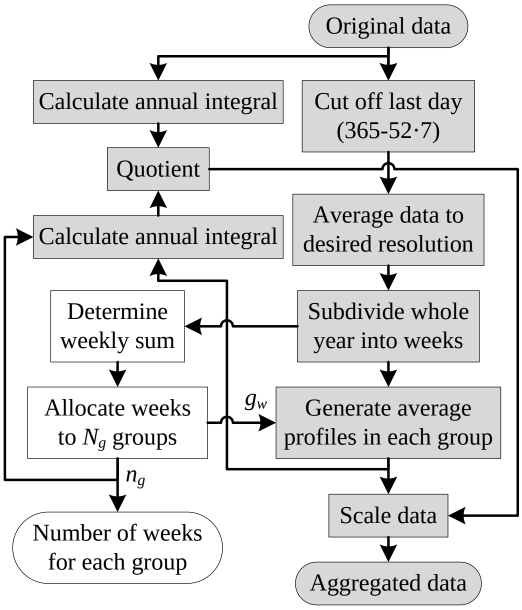

Figure 1
Aggregation algorithm illustrated exemplary for a period length of 7 days

similar weeks. In this sense, each week is allocated to one group according to its weekly sum. The information of this allocation is stored in vector g_w and used for generating the typical profiles. Additionally, the number of weeks in each group is determined and provided to the optimization model as a parameter n_g.

In the next step, based on the weekly subdivided (but not weekly averaged) data, typical-week profiles are generated by averaging over all weeks that are aggregated in one group. For instance, the value of the first time step of a typical profile results from the average over all first time steps of the weeks in this particular group. Hence, the typical profile preserves the average weekly demand as well as the main characteristic of the trends in this group. Finally, a compensation for the time steps which have been cut off in the first step is performed. For this purpose, the generated profiles are scaled by the quotient of the annual integral of the synthetic and the one of the original data. As a result, the annual integral of the aggregated time series $dat_{g,h}^{aggr}$ equals the annual integral of the original data, dat_{ty}^{orig} according to the following equation:

$$\frac{15}{60}\,\mathrm{h}\cdot\sum_{t_y} dat_{t_y}^{\mathrm{orig}} = \Delta t\cdot\sum_{g}\left(n_g\cdot\sum_{t} dat_{g,t}^{\mathrm{aggr.}}\right) \quad (1)$$

with n_g the number of profiles aggregated in group g, and t_y the time steps based on the whole year. The final data are written in a g-by-t matrix and saved into an include-file, which is provided to the optimization model as well.

Since the number of weeks in each group must be the same for all different time series used in the optimization model, the algorithm is only performed for the heat demand profile. For all other time series, the allocation g_w is kept constant. Preliminary investigations have shown that the arrangement g_w is similar for the 3 different heat demand profiles, which is plausible because it is mostly affected by the seasonality of the heating demand profiles. Therefore, only the typical-data-generation part of the aggregation algorithm, which is indicated by grey filling in Figure 1, is performed on all other series. The reason for choosing the heat demand profile for the leading aggregation is the clearer seasonality in comparison to the electrical demand profile.

Numerical Analysis

In this section, the time series aggregation methods are evaluated based on the relative accuracy and time saving. For this purpose, the optimization model is solved several times with aggregated and **unaggregated input data**. An extensive sensitivity analysis confirms an increase of the relative deviation with lower intra-day temporal resolution. Due to the minimal load constraints during intermittent operation the utilized storage capacity is higher at lower intra-day temporal resolution. Thus, the capital costs for the thermal storage rise and fuel costs increase because of higher heat losses at the thermal storage. Furthermore, the aggregated demand profiles have fewer variations, so that electricity purchase and feeding-in occur less often, which leads to a cost-decreasing effect that is less dependent from the temporal resolution. Due to the superposition of both effects, choosing a higher temporal resolution does not always result in higher accuracy. A simple comparison reveals that in average, a weekly aggregation achieves shorter solving times and higher accuracies compared to daily aggregation.

The effect of the aggregation period length on the accuracy is investigated in a further sensitivity analysis. For this matter three different setups are optimized for a multi-family house and an apartment building. In the first setup only a boiler (BOIL) can be selected, in the second a PV system in addition to the boiler and the third setup pre-sets the additional installation of a battery (BAT) storage system. Each setup is optimized once with unaggregated input data and 7 times with differently aggregated data. In this case the aggregation is done by 7 typical profiles (7 groups) with 60 min resolution. The period length of those aggregated profiles is varied from 1 to 7 days. Figure 2 shows the relative deviation of the objective function value based on the corresponding optimization result with unaggregated data plotted against the period length. The trends show a steep decrease until a specific point, from where it is almost flat. Hence, an extension of the period length reduces the relative deviation, but above a specific period length further extensions bring no significant enhancement of the accuracy. This is plausible,

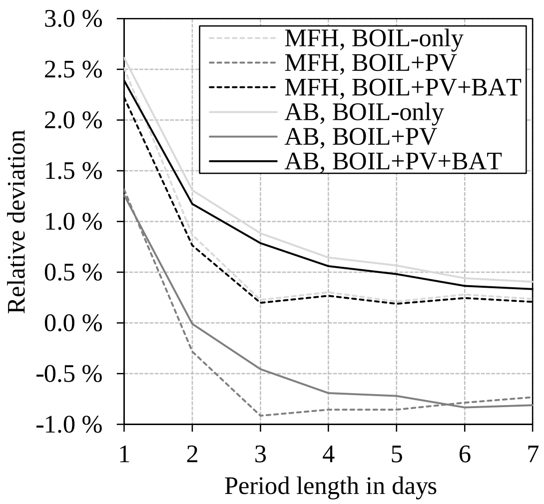

Figure 2
Sensitivity analysis about the effect of the period length on the accuracy of the optimal solution

because with 1-day aggregation the possibility of storing heat over subsequent days is being neglected, so 2-daily aggregated time series provide more valid input data. However, storing energy over periods longer than 3 or 4 days is economically inefficient. Therefore, there is no significant difference between the deviations at 5 and 7 days period length. Consequently, under consideration of the computing time, aggregations around period lengths of 3 days are expected to be most efficient. The graphs also indicate that this specific point depends on the type of building, i.e. the characteristic of the heat demand profile. Further investigations show that with the same input data, the accuracy and especially the relative time savings are subject to high fluctuations depending on the technology choices and type of buildings. Therefore, the final investigation comprises several optimizations of 12 different setups to determine the average values of the accuracy, i.e. absolute value of the relative deviation, and the relative solving time. Each setup is optimized with unaggregated data as a reference and 17 times with differently aggregated time series. In this regard all 3 parameters of the aggregation algorithm , i.e. period length, number of groups and intra-day temporal resolution, are varied in certain ranges, so that the number of time steps lies between 500 and 1000. In Figure 3 the relative solving time is plotted against the accuracy of the MIP solution. Both are averaged over all 12 setups. However, each point represents a different aggregation method.

The shape of the point cloud represents the trade-off correlation between short solving time and high accuracy. The markers shape indicates the period length; the colour represents the number of groups while the size illustrates a different intra-day temporal resolution. It stands out that the larger markers, which represent a 60 min resolution, are

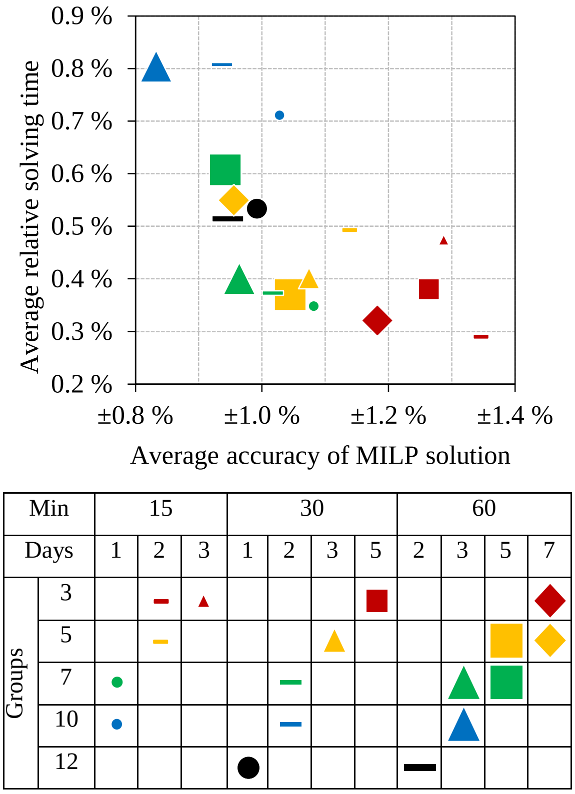

Figure 3
Relative solving time and accuracy of aggregation methods averaged over 12 different model setups

mostly located on the left-bottom edge of the point cloud. This indicates that a lower temporal resolution at 60 min leads, as expected, to a more efficient solving process than higher resolutions The results further reveal that multiple day aggregation enables a more accurate optimization result than the conventional typical day aggregation and has the potential to offer a more efficient solution with respect to both accuracy and time saving. Still, a high uncertainty regarding the solving time has to be considered in terms of optimizing different setups. The typical 3-days aggregation with 7 groups and 1 h resolution is identified as the optimal aggregation setup. The latter allows for reducing the computing time by 94 % compared to typical-day aggregation with 15 min resolution, where each month is represented by one averaged profile, while retaining a minimal accuracy deviation of ±0.96 % based on an unaggregated reference. The total computing time reduction based on unaggregated references reaches 99.6 % in average. The most accurate aggregation considered in this investigation that corresponds to 3 days with 10 groups and 15 minutes results in an average deviation of ±0.83 % and total time saving of 99.2 % based on references. In comparison, the advanced method presented by Fazlollahi *et al.* (2014) achieves a relative deviation of 0.7 % and 97.5 % time saving based on unaggregated reference.

OPTIMIZATION MODEL

The MIP model extends the approach from our previous work to optimize the energy systems of several buildings within a residential district. The objective function formulated as the total annual costs, is minimized subject to a set of economic and technical constraints. The extensions comprise the introduction of a local heating network (LHN) and microgrid (MG) connections. The electrical demand profiles are generated based on the model provided by Richardson *et al.* (2010), which considers a combination of patterns of active occupancy in domestic buildings. The heat demand profile comprises space heating and domestic hot water demand. The first is based on a 2-capacities building model. The hot water profile is determined using the model by Jordan and Vajen (2003). The annual demands are given in Table 2 in the Appendix.

Economic Constraints

The capital costs are considered by the annualization of the investments for all installed technologies. The investments for energy conversion units and LHN are calculated based on assumed capacity specific or length specific investments respectively (compare Table 3). For a MG, an investment for a central control unit is assumed proportional to the number of buildings. While each LHN connection is optional, the decision for a MG is set collectively. Demand related costs consider expenses for gas and electricity purchase from the public grid. Furthermore, service costs and other costs are considered (compare Table 3and Table 4). The revenues generated by CHP units comprise sales related and production related shares (CHP-index and CHP Subsidy in Table 4). Additional costs for the EEG apportionment, which is charged for self-consumed CHP power according to BMWi (2014) are included. An exclusion from those charges is possible for at most 10 $\mathrm{MWh_{el}}$ during 20 years (after installation) if the installed CHP capacity is at most 10 $\mathrm{kW_{el}}$, which is implemented by additional constraints.

Technical Constraints

The technical constraints comprise physical correlations and boundaries of the considered technologies according to our former work.

Microgrid

The establishment of a MG is symbolized by a collective decision parameter to maintain linearity and reduce the complexity of the optimization model. Mathematically the implementation of the MG is represented by a summation within the electricity balance over all buildings. The electricity balance for each building is illustrated in Figure 4. Besides the main electricity balance (EB), a secondary balance for HP and EH is defined, which is fed by electricity bought at HP tariff $\dot{E}_i^{\mathrm{buy,HP}}$ and self-produced electricity $\dot{E}_i^{\mathrm{self,HP}}$. This allows for PV and CHP

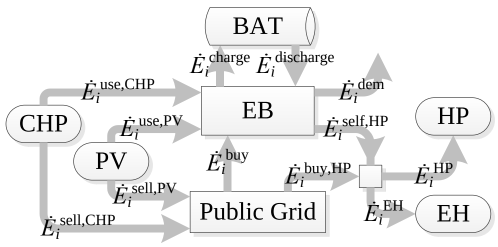

Figure 4
Electricity balance

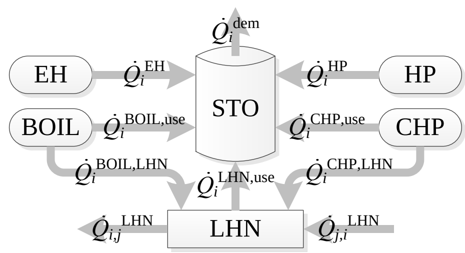

Figure 5
Heat balance

power to be consumed by the HP & EH, while the power from the HP tariff circuit is exclusively consumed by the HP and the EL.

Local Heating Network

The model of the LHN is based on a simplified approach considering building-to-building connections and energy flow rates interactions. Due to relatively short distances between the neighbouring buildings, thermal losses are neglected. Our former work considered pressure losses due to friction in pipes, built-in components and heat exchangers within the buildings. The results revealed that the electricity costs for pumping amount to 0.15 % of the total annual costs. Consequently, in this model friction losses are neglected and the pipe diameter options are reduced to one for minimizing the computational effort. Further, the LHN is designed as unidirectional network, i.e. energy can only flow in one direction. Since HPs operate less efficient on high feed temperature, only CHP and boilers are considered to supply the LHN. Therefore, the heat productions of CHP and boiler are split up into fractions for own usage and for the LHN as illustrated in Figure 5. Additionally, a design heat load balance for each building is implemented, where an exchange via LHN is allowed but not with thermal storages.

SIMULATION RESULTS

In the following sections different setups representing certain combinations of technologies are investigated with subject to cost optimal design. For this matter, presets (additional constraints) are implemented that prohibit the selection of technologies that should not be considered in the certain case. For instance "BOIL+PV" represents a preset in which besides a conventional boiler and thermal storage also PV can be selected. The other technologies are prohibited by setting their binary decision variables to zero. For comparison with alternative setups a reference setup is optimized for each building. For this purpose the preset "BOIL-only" is chosen. It states that a conventional boiler is the only possible heat source. A thermal storage is still optional whereas a battery storage system is excluded from this setup. The optimality criterion is set at 0.1 %. It turns out that the boiler capacities for building (AB) fit to the corresponding design heat loads. In case of the single-family house (SFH) the smallest considered boiler capacity is selected. A thermal storage with small capacity is installed in each building.

Heat Pump and CHP

Investigations of single-building configurations show that HP operation is economically not efficient enough to compete with a condensing gas boiler. In contrast, CHP units achieve significant cost savings in MFH and AB, because the major share of electricity demand is covered by self-produced power at relatively low levelized electricity cost (LEC).

The implementation of a MG allows for heat pumps to run on electricity generated by local CHP unit in another building. Furthermore, connections via a LHN enable higher work load for CHP units and/or the installation of larger units, which leads to lower specific energy costs. Previous investigations for a neighbourhood with 2 SFHs, 2 MFHs and 2 ABs show that by introducing a MG the costs for a setup with boiler, CHP and HP can be reduced by 0.7 %. Instead the introduction of a LHN achieves 4.6 % cost reduction. The combination of both is more efficient and is investigated in this work.

Aligning with our previous work a district in the German city Bottrop with 2 SFHs, 3 MFHs and 1 AB is considered for the following investigations (compare Figure 6). With the simulation of MG and LHN the computational effort increases rapidly. Consequently, additional preset constraints are implemented in the optimization model to reduce the solution space. PV and battery storage systems are excluded. Additionally, unfeasible LHN connections are forbidden. These are: 3↔6, 3↔5, 4↔6, 2↔6, 1↔5, 1↔6 and 2↔3. The total number of connections is limited to 5. Furthermore, CHPs are not allowed in the SFHs, since it is more efficient to place them in buildings with higher heat demand. The installation of any CHP unit is enforced in the AB. Additionally, based on simulation results of less complex systems a start solution is provided to the solver to reduce the solving time. It comprises a 15 kW_{el} CHP unit in building 1, a 4.7 kW_{th} HP in building 3 and 8.4 kW_{th} HPs in building 5 and 6. According to the resulting optimal layout in Table 1 one 15 kW CHP unit in the AB provides the whole district with thermal energy via a LHN. Boilers in the

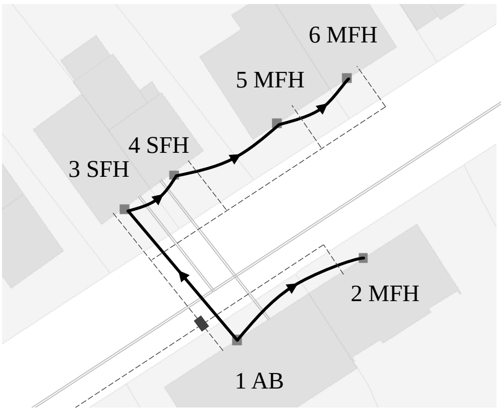

Figure 6
Optimal LHN layout with a MG

SFHs and HPs with EHs in the MFHs provide additional power during high heat demand periods. Since the buildings 2, 5 and 6 comprise electrical devices, only 3 buildings require gas grid connections. As a result, the total annual costs amount to 43,189 €/a, which implies 10.3 % cost savings based on the reference setup. The carbon dioxide emissions are reduced by 33.6 %. Without any connections the cost saving are limited to 1.3 %.

Besides these results, the limitations of this methodology need to be considered. Due to long solving time the optimization of the 6- buildings configuration with MG and LHN is performed until a relative optimality gap of 3.7 % is reached, i.e. the annual costs of the presented solution are at most 3.7 % higher than those of the global optimum. For instance, moving the boiler from building 3 to building 1 as a peak boiler saves 233 €/a due to lower investment and one gas grid connection less, which complies with 0.85 % of the total costs. Since this lies within the gap, this improvement is not considered in the presented solution. Alternatively, merging the two 9 kW boilers into one 18 kW unit can save 1.1 % of the total annual costs, but this also increases the minimal load of the system. In turn, more frequent intermittent operation affects higher storage utilization. Furthermore, the analysis of the simulation data reveals a slight oversizing of the electrical heating elements (ELH) by 1.7 kW. An adjustment reduces the total annual costs by only can be recognized between the capacity ratios 2 and 4. Furthermore, the results of the setups with MG and 3 €/a, which is why this oversizing is tolerated in regard to the optimality gap. The high economic efficiency of this setup is due to the large CHP unit installed capacity and its synergy with the HPs. As a result low demand related costs are achieved. 90.1 % of HP and EH consumption is covered by the CHP unit, which is 31.2 % of the whole CHP electricity production. The CHP unit reaches 4104 full load hours per year.

A further investigation analyses combinations of different buildings and whether a certain ratio between HP and CHP capacities can be identified as cost-optimal. In this regard, several combinations of the 3 different types of building are optimized, to examine the cost optimal CHP-HP capacity ratios. To maintain manageable solving time, configurations with 2 to 6 buildings are considered. For a comparison between the different configurations combined levelized electricity and heat cost (LEHC) is introduced. It is determined from the total annual costs divided by the total annual electricity and scaled heat demand, as presented in equation (2). By scaling the annual heat demand, it is considered that heat has a lower economic value compared to electricity. Therefore the scaling factor $f^{\mathrm{Q/E}}$ is calculated from the quotient of the specific demand related heat costs and the specific electricity costs based on the reference setup (BOIL-only). The LEHC is calculated for each optimal solution of the considered building configurations and plotted against the CHP-HP capacity ratio, which complies with the quotient of total CHP and HP electrical capacity.

$$LEHC = \frac{c^{\mathrm{t}}}{\sum_i \sum_g \left[n_g \cdot \sum_t \left(\dot{E}^{\mathrm{dem}}_{i,g,t} + \dot{Q}^{\mathrm{dem}}_{i,g,t} \cdot f^{\mathrm{Q/E}} \right) \Delta t \right]} \quad (2)$$

Figure 7 shows that without LHN the optimal designs comprise a wide range of capacity ratios between 1 and 8. Additionally, the size of the markers indicates the total sum of CHP and HP (electrical) capacities in a certain configuration, to consider the economics of

Table 1
Optimization results for the considered district with / without connections (rel. gap 3.7 %)

Position *i*	1	2	3	4	5	6
Type of building	AB	MFH	SFH	SFH	MFH	MFH
cap_i^{STO} in m³	0.97 / 1.04	1.10 / 0.17	0.27 / 0.06	0.33 / 0.07	1.10 / 0.19	1.10 / 0.17
cap_i^{BOIL} in $\mathrm{kW_{th}}$	- / 24.5	- / 25.7	9 / 9	9 / 9	- / 25.7	- / 25.7
$cap_i^{\mathrm{CHP,inst}}$ in $\mathrm{kW_{el}}$	15 / 3	- / -	- / -	- / -	- / -	- /-
$cap_i^{\mathrm{HP,inst}}$ in $\mathrm{kW_{th}}$	- / -	11.4 / -	- / -	- / -	11.4 / -	4.7 / -
cap_i^{ELH} in $\mathrm{kW_{th}}$	- / -	17.4 / -	- / -	- / -	17.4 / -	16.5 / -

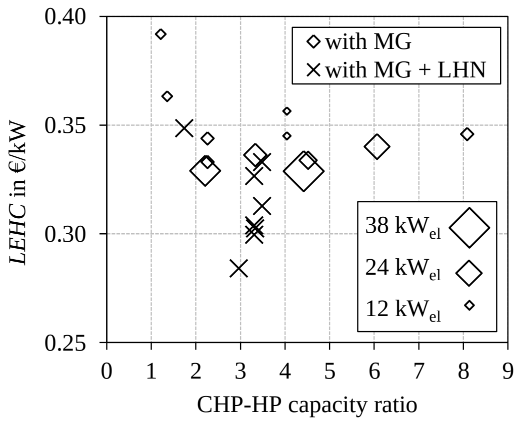

Figure 7
Levelized electricity and heat costs at different CHP-HP capacity ratios

scales. With this in mind the tendency of a minimum LHN, which are represented by the crosses, show that those CHP-HP capacity ratios mostly take values around 3.5. This is plausible, because with the additional options for LHN pipelines, the model provides more flexibility for the design optimization. Therefore, energy systems with LHN options are designed closer to the optimal capacity ratio.

CONCLUSION

This work presents a MIP approach for the cost optimal design of energy conversion units in a domestic district.

Further, different time series aggregation methods are investigated to reduce the computational time. The results reveal that a multi-day aggregation enables shorter solving at times while conserving the accuracy, due to the consideration of inter-day energy shifting. As an appropriate trade-off between solving time and accuracy, an aggregation by 7 typical 3-days profiles with 1 h intra-day temporal resolution is chosen for the MIP investigations in this work. This setup reduces the solving time by further 94 % compared to a typical days aggregation method based on monthly average profiles, i.e. 99.6 % based on unaggregated reference. The accuracy averages at ±0.96 %.

In terms of CHP and HP installation, optimizations for several configurations reveal significant enhancement of the economic efficiency of distributed energy systems by introducing a MG and LHN. The optimal design of an exemplary district comprises one large CHP unit supplemented by HPs, electrical heater and boilers to cover base and peak demands. Due to the MG, the HPs and electrical heaters operate on low cost electricity from the CHP unit. As a result the total annual costs are 10.3 % lower than in the reference setup. Also, carbon dioxide emissions are reduced by 33.6 %. A thorough sensitivity analysis show that for larger districts a ratio between the total installed CHP capacity and HP capacity around 3.5 is can be expected to achieve the highest economic efficiency.

ACKNOWLEDGEMENT

Grateful acknowledgement is made for the financial support by E.ON gGmbH.

APPENDIX

Table 2
Energy demands (Verein Deutscher Ingenieure (2006), BDEW (2010))

type	Heat.	Hot w.	Elec.	DHL	Pers.
	in kWh/a			kW	-
SFH	13,029	1,271	3,168	6.5	2
MFH	44,020	5,086	9,410	25.7	8
AB	46,845	14,621	25,590	33.5	23

Table 3
Cost parameters (Harb *et al.* (2014), Mehleri *et al.* (2013), Spieker and Tsatsaronis (2011), LOGSTOR Deutschland GmbH (2014))

tech	Fixed inv. (excl. VAT)	Variable inv. (excl. VAT)	Service costs
STO	500 €	1450 €/m³	-
BOIL	3100; 600 €	62 €/kW	3 %/a
CHP	-	7750; 5895; 4381; 3214; 2777; 2442 €/kW_{el}	8 %/a
HP	4744.6 €	562.28 €/kW_{th}	2.5 %/a
ELH	245 €	19 €/kW	-
LHN		(40+100) €/m	4.4 %/a
MG		300 €/building	

Table 4
Tariffs and subsidies (ELE GmbH (2014b), ELE GmbH (2014a), ELE GmbH (2014c), EEX AG (2014), Bundesministeriums der Justiz und für Verbraucherschutz (2002), Bundesnetzagentur (2014a), Verbraucherzentrale NRW (2014), Bundesnetzagentur (2014b))

	Work price	Base price
Electricity	27 ct/kWh_{el}	101.76 €/a
HP Elec.	23.94; 20.19 ct/kWh_{el}	65.45 €/a
Gas for Boiler	7.84 ct/kWh_{LHV}	121.44 €/a
Gas for CHP	7.23 ct/kWh_{LHV}	
CHP-index	5.13; 4.16; 4.78; 4.65 ct/kWh_{el}	-
CHP Subsidy	5.41 ct/kWh_{el}	-
EEG for CHP	0.3827 · 6.24 ct/kWh_{el}	-
$Refund_{avoid\text{-}grid}$	0.9 ct/kWh_{el}	-
PV Feed-in	12.75 ct/kWh_{el}	-

Table 5
Capacity choices (Spieker and Tsatsaronis (2011), proKlima (2014), Brötje GmbH (2014), Bosch Thermotechnik GmbH (13/10/14), Enertech GmbH (2014), Viessmann Werke GmbH & Co. KG (2014))

tech	**Available capacities**	**Min. load**
STO	0.06 - 2 m³	-
BOIL	9 - 40 kW	25 %
CHP	2; 3; 5; 10; 15; 20 kW_{el}	50 %
HP	4.7; 6.2; 8.4; 11.4; 17.2; 24 kW_{th}	40 %
ELH	0 - 30 kW	-
PV	1.5 - 50 m²[19]	-
BAT	5; 8.1; 9.2; 20.5 kWh	-

REFERENCES

Bundesministeriums der Justiz und für Verbraucherschutz (2002) Gesetz für die Erhaltung, die Modernisierung und den Ausbau der Kraft-Wärme-Kopplung KWKG.

BMWi (2014) Gesetz für den Ausbau erneuerbarer Energien (Erneuerbare-Energien-gesetz). EEG.

BDEW (2010) Energieverbrauch im Haushalt (5 May 2014).

Bosch Thermotechnik GmbH (13/10/14) Buderus, http://www.buderus.de/sixcms/detail.php/2231640?prod[Produkte]=2231110

Brötje GmbH (2014) Trinkwassererwärmer, https://www.broetje.de/de/trinkwassererwaermer

Bundesnetzagentur (2014a) Press release: EEG-Umlage beträgt im kommenden Jahr 6,24 ct/kWh

Bundesnetzagentur (2014b) EEG-Vergütungssätze August und September 2014 (17 Jul 2014).

Cardoso, G., Stadler, M., Siddiqui, A., Marnay, C., DeForest, N., Barbosa, A., and Ferrão, P. (2013) Microgrid reliability modeling and battery scheduling using stochastic linear programming. Electric Power Systems Research, **103**, 61–69.

Domínguez-Muñoz, F., Cejudo-López, J. M., Carrillo, A., and Gallardo, M. (2011) Selection of typical demand days for CHP optimization. Energy and Buildings, **43**(11), 3036–3043.

EEX AG (2014) KWK-Index, Phelix Quarterly (28 Apr 2014).

ELE GmbH (2014a) Auftrag ELE Wärmepumpenstrom (29 Apr 2014).

ELE GmbH (2014b) Produktblatt ELE strom 2015.

ELE GmbH (2014c) Produktblatt ELE erdgasPur.

Enertech GmbH (2014) Speichersysteme GiegaThem http://www.giersch.de/produkte/speichersysteme/speichersysteme-giegatherm/did_2002924.html.

Evins, R. and Orehounig, K. (2014) A Bi-Level Design and Operation Process Applied to an Energy Centre. BSO 2014.

Fazlollahi, S., Bungener, S. L., Mandel, P., Becker, G., and Maréchal, F. (2014) Multi-objectives, multi-period optimization of district energy systems: I. Selection of typical operating periods. Computers & Chemical Engineering, **65**, 54–66.

Haikarainen, C., Pettersson, F., and Saxén, H. (2013) An MIP Model for Distributed Energy System Optimization. Chemical Engineering Transactions.

Harb, H., Reinhardt, J., Streblow, R., and Müller, D. (2014) Optimal design of energy conversion units for resitdential houses. BSO 2014.

Harb, H., Reinhardt, J., Streblow, R., and Müller, D. (2015) MIP approach for designing heating systems in residential buildings and neighbourhoods. Journal of Building Performance Simulation.

Jordan, U. and Vajen, K. (2003) Handbuch: DHWcalc. Werkzeug zur Generierung von Trinkwasser-Zapfprofilen auf statistischer Basis.

LOGSTOR Deutschland GmbH (2014) LOGSTOR Brutto-Preisliste 2014.

Mehleri, E. D., Sarimveis, H., Markatos, N. C., and Papageorgiou, L. G. (2013) Optimal design and operation of distributed energy systems: Application to Greek residential sector. Renewable Energy, **51**(0), 331–342.

proKlima (2014) Gas-Brennwertkesselliste

Richardson, I., Thomson M., Infield, D., and Clifford, C. (2010) Domestic electricity use: a high-resolution energy demand model.

Spieker, S. and Tsatsaronis, G. (2011) Dimensionierung von Mini-KWK-Anlagen zur Teilnahme am liberalisierten Strommarkt. VDI Berichte, Optimierung in der Energiewirtschaft(2157), 241–258.

Stojiljković, M. M., Stojiljković, M. M., and Blagojević, B. D. (2014) Multiobjective Combinatorial Optimization of Trigeneration Plants Based on Metaheuristics.

Veeramsetty, V. (2014) Optimal allocation of distributed generation deployment in distribution network using PSO. Energy Challanges and Mechanics.

Verbraucherzentrale NRW (2014) Blockheizkraftwerke: Vergütung des erzeugten Stroms, http://www.vz-nrw.de/BHKW-Verguetung.

Verein Deutscher Ingenieure (2006) VDI 2067 Part 12, Economic efficiency of building installations: Effective energy requirements for heating service

Viessmann Werke GmbH & Co. KG (2014) Warmwasserspeicher, http://www.viessmann.de/Produkte/speicher-wassererwaermer.html.

Weber, C. and Shah, N. (2011) Optimisation based design of a district energy system for an eco-town in the UK. Energy(36), 1292–1308.

Zhou, Z., Liu, P., Li, Z., and Ni, W. (2013) Economic assessment of a distributed energy system in a new residential area with existing grid coverage in China. Computers & Chemical Engineering, **48**(0), 165–174.