Energy Proceedings
Vol 27, 2022
ISSN 2004-2965

Cost Optimization Model and Management Strategies for Distributed Energy Resources in Industrial Microgrids#

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ABSTRACT

This study applies a distributed energy resources scheme on industrial microgrids and provides a case study that is based on the Component-oriented Modeling and Optimization for Nonlinear Design and Operation (COMANDO). The model comprises distributed energy resources commonly used by industrial enterprises (i.e., solar power, combined-heat-and-power, heat pumps), energy storage systems, and management strategies (peer-to-peer trading, bulk purchasing). To demonstrate the model, a case study is conducted for a real-world industrial area in Germany. We find that the economic impact of the various strategies is highly dependent on the specific demand curves. However, combining the DER and the stated management strategies is always profitable and leads to reductions of a global warming index used as an ecological indicator.

Keywords: microgrid, district heating, distributed energy resources, peer-to-peer trading

NOMENCLATURE

Abbreviations	
a	year
B	Boiler
BAT	Battery
BAU	Business-as-usual
CHP	Combined Heat and Power
COMANDO	Component-oriented modeling and optimization for nonlinear design and operation
DES	Decentralized energy systems
DER	Distributed energy resources
ED	Electric demand
ESS	Energy storage systems
GD	Gas demand
GW	Gigawatt
GWI	Global warming index
GW_p	Gigawatt peak
h	Hour
HD	Heat demand
HP	Heat pump
IES	Industrial energy system
IMG	Industrial Microgrid
MG	Microgrid
NPV	Net present value
P2P	Peer-to-Peer
PD	Power demand
PV	Photovoltaic
RE	Renewable energy
RES	Renewable energy system
ROI	Return on investment
HWS	Hot water storage
TSA	Time series aggregation
Symbols	
BC	Battery capacity
c_i	Costs of component i
c_{ref}	Reference cost
Eq	equivalent
I	Firm I
IN	Input
K	Firm K
kt	Kiloton
M	Cost escalation factor
m	Market electricity price
OUT	Output
S	Fixed cost parameter
Q_i	Output of component i
Q_{ref}	Reference output
u	Utility electricity price
Z	Firm Z

z	Electricity price participant Z

1. INTRODUCTION

Global microgrid capacity is expected to rise from some 3.5 GW in 2019 to 20 GW by 2028. Still, little research has been done on modeling distributed energy resources in industrial microgrids (IMG).

To be able to make a strong case for distributed energy resources (DER) as a factor in fighting climate change, it must be shown that the technologies are profitable and have the potential to help to significantly slow down global warming. However, first it should be proven that Germany has the capacity to implement the necessary amount of DER.

A study examining the rooftop photovoltaic (PV) potential for the city of Dresden and Germany overall is [1]. It shows that the capacity needed for establishing a climate-neutral energy system in Germany (387 GW_p) was surpassed by 30%, estimating the overall rooftop potential at 500 GW_p.

After showing that Germany would have the capacity for enough DER, [2] discusses the economic aspects of integrating DER in industrial areas. The authors optimized energy equipment sizing, including electricity and thermal power – for a Spanish industrial site under the objective of minimizing the net present value (NPV). The optimality results predicted payback periods of less than five years.

A possible way to further increase the benefits of and interest in DER could be peer-to-peer (P2P) trading. Applied to energy, it enables participants to trade energy with each other through a microgrid, more or less independently from the usage tariffs paid when using the utility grid.

Having chosen a three-layer P2P electricity trading system, [3] showed the monetary benefits of P2P trading for communities with high penetration of household distributed PV. The results show that within a single day, 62.5% of the surplus PV electricity of all prosumers could be consumed within the community. Through P2P electricity trading of this part of electricity, total revenues of prosumers were increased by 11.5%, and total expenditures of all users decreased by 7.5%, resulting in a decrease of the net expenditures of the whole community by 13.8%.

P2P trading in general is physically possible between all users connected to the same grid but is restricted through the regulations on grid operators. To reduce the outer control of the trading there is the possibility to manage multiple demands and suppliers of power in a so-called microgrid (MG). In research in this field, this is a commonly used concept. Advantages and barriers of MGs were shown in a systematic mapping in which research trends of industrial smart and microgrids were assessed (Brem *et al.*, 2020). One major finding of the study is that future research should focus on incorporating energy storage systems (ESS) into existing systems to optimize financial performance.

The research concerning DER in different scenarios of usage is widespread, covering all known concepts of usage and technologies available. Still, to our best knowledge, a case study for a German industrial microgrid including all the relevant technologies and management strategies does not yet exist in the literature. Such a study could be very useful for industrial players interested in reducing their negative impact on the environment, whilst staying economically competitive.

The literature review showed that little research exists on the integration of DER in German industrial areas. This study is supposed to add to the literature, reducing uncertainties of potential industrial users. In our study, we want to provide more information on the industrial usage of DER, evaluate its benefits, and outline ways of integrating DER into existing energy systems. We show the feasibility of using renewable energies in industrial areas and the positive effects that this would have on the environment. Besides the reduction of uncertainty, we also quantify the effects of P2P trading on economic and environmental criteria, compared to using DER separately. This is done to increase legislators' interest in creating legal frameworks for using P2P. Overall, we hope to fasten the diffusion of renewables in industrial applications. To do so, an optimization model was developed, allowing the virtual design and operation of industrial energy systems.

The model comprises DER commonly used by industrial enterprises (i.e., solar power, combined-heat-and-power/CHP, heat pumps/HP), ESS, and management strategies (P2P trading, bulk purchasing). To demonstrate the model, a case study was conducted for a real-world industrial area in Germany. The IMGs power and heat demand are modeled through a mix of synthetic standard load profiles and actual data obtained from the case study participants. Generation profiles of the solar DER are based on meteorological data for the area. In the optimization, the economic and greenhouse gas emissions effects. The latter is measured by the Global Warming Index (GWI) of the various management strategies for the technology combinations considered, resulting in an optimal DER mix to be installed in the industrial area of interest. The GWI is computed by summing up the emissions of the DER operation and the emissions of the energy taken from the grid.

2. MODEL SPECIFICATION

In this study, an already existing energy system optimization model for a university campus is adapted for optimizing an industrial area in Germany with multiple users of the same energy system. To that end, a case study with three industrial users was conducted. For reasons of confidentiality, the firms are named I, K and Z. First, the changes made to the original model are explained, followed by a short description of the case study conducted.

The optimization is based on the industrial energy system (IES) case study reported in [4] which itself is based on [5]. The model was formulated in Python, an open-source programming language. The application is divided into two sections: building the model and running it. The former starts by creating an energy system in which all components considered in the optimization are integrated: Electricity demand (ED); Heat demand (HD); Power demand (PD); Gas demand (GD); Boiler (B); CHP; HP; PV; Battery (BAT); and Hot water storage (HWS).

Each component exists only once and is assumed to be used jointly if necessary. This is because, under the current German legislation, there can only be one energy supplier per consumer [6]. This led to the idea of using an MG managed by an energy hub operator internally, having only a single connection point to the utility grids for gas and electricity. The assumption is based on [7]. Besides the legal aspect, [8] finds that sharing a Renewable energy system (RES) might make even better use of diverse demand and generation patterns. The components also inherit a binary variable, determining if a component is built in the optimization or not [4].

The components need to be parametrized before use. They can be separated into demand, generation, and storage. The demand components are described first. Electricity and heat demand are both components specified as load time series of one or multiple firms, introduced later in the data set. Residual power and gas loads are those capacities that the MG needs to take from the public grid in order to satisfy all demands that cannot be supplied internally. Next, the generation components are parametrized. Characteristics of generation components are that they need to be purchased and that they generate useful energy from input not exploitable by the user. Therefore, all of these components have a cost and efficiency function. Some of the components are also characterized by specific part-load behavior. This is the case when efficiency changes, i.e. when a component is used at less than maximal load. Part-load behavior is described individually for the respective components. The cost functions for all components except the battery are assumed to be non-linear and must be linearized by COMANDO during the solving. The cost functions are determined by the output variable Q of component i divided by the reference output $Q_{\text{ref,i}}$ raised to the power of M and multiplied by the reference cost $c_{\text{ref},i}$ (Eq. 1), i.e.:

$$c_i = \; c_{ref,i} * \left(\frac{Q_i}{Q_{ref,i}}\right)^M. \qquad (1)$$

The efficiency determines the output generated from the input and is specific to each component.

The boiler generates heat from burning gas, thus using gas as an input and producing heat as the output. Its cost function is set to zero since all participants already operate boilers capable of providing their own heat demand. Therefore, no further investment is needed. The boiler´s efficiency and its part-load behavior are taken from [9].

The HP uses electricity and energy from ambient air to produce heat. Only electricity is considered as an input since air is usually freely available. Heat is the output. The cost function is taken from [5], with a slightly higher cost exponent, due to prices observed in the heat pump market when the study was conducted. The ambient temperature for operation is taken from the COMANDO data set. The temperature of output heat can be chosen individually and differs between firms since one is heating through floor heating (40 °C) while the other uses radiators for heating (70 °C). When the component is used jointly the less energy-efficient configuration with 70 °C is assumed.

CHP units generate electricity and heat from a gas turbine. As gas is the input, the component has electricity and heat as outputs at a fixed ratio. The parametrization was again adopted from [5], including three predefined sizes of the CHP unit with different ranges for the nominal capacity, as in [4]. This accounts for the size dependency of the conversion efficiencies for heat and electricity. The three CHP models are aggregated into a subsystem, which enforces that at most one of them is being built.

Since the parametrization is based on data from 2019 or older it was found that costs for PV had changed drastically. This led to a change in the cost parameter c_{ref}. Offers of regional PV suppliers were used to reevaluate the parameter. Capacity is based on the available rooftop size and differs for the different users. Free-field PV is not considered.

The battery storage unit is charged and discharged with electricity and defined through charging and discharging efficiencies. The only major change was made to the cost function. A market review of 181 batteries resulted in a linear cost function (ordinary least squares regression). A fixed cost parameter S was added to the multiplication of the reference cost c_{ref} and the variable battery capacity BC, i.e.:

$$c_{bat} = S + c_{ref} \cdot BC \quad (2)$$

Hot water storage uses the same functionality as the battery and thus a similar parametrization was adopted. The maximum capacities of the storage units are restricted to reasonable sizes since the weighted sum method, which is used in COMANDO, always favors maximal storage when only the environmental objective is considered.

After parametrizing all components, they are connected to energy balances. Balances for power (Eq. 3), gas (Eq. 4), and heat (Eq. 5) are deployed. The balances do not allow for residuals, thus all energy outputs from a Decentralized energy systems (DES) must be consumed by others in the same balance. IN and OUT determine if energy is consumed or provided by a DES. The connections of the components are shown in Fig. 1.

$$0 = Q_{POWER.OUT} + Q_{ED.IN} + Q_{BAT.IN} + Q_{BAT.OUT} + Q_{HP.IN} + Q_{CHP_{Power}.OUT} + Q_{PV.OUT} \quad (3)$$

$$0 = Q_{CHP.IN} + Q_{B.IN} + Q_{GAS.OUT} \quad (4)$$

$$0 = Q_{HD.IN} + Q_{STH.IN} + Q_{STH.OUT} + Q_{HP.OUT} + Q_{CHP_{Heat}.OUT} + Q_{B.OUT} \quad (5)$$

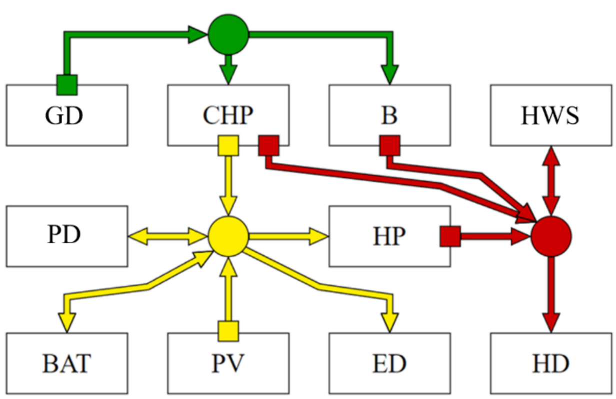


Fig. 1 Energy flows in the DES investigated

3. DATA USED

The case study relies on multiple types of input data, differing in source, quantity and time of acquisition. The differences between data sets and the choice of specific subsets of the data are explained next.

Starting with the data sets, the study uses data for solar irradiation, ambient temperature and the demands for heating and electricity. Data for the solar irradiation was taken from the HelioClim-3 database, which is derived from satellite data. The data was summoned for the location of an industrial park (in the German federal state of North-Rhine Westphalia) for the time period Jan 1, 2006 to Dec 31, 2006. The year 2006 was chosen because it does not count among the ten hottest years measured, which all occurred after the year 2000. This was done to protect the data from being seen as biased towards renewables, which benefit from higher irradiation. The global irradiation on the horizon was chosen to account for weather influence (clouds, dust etc.). The ambient temperature was taken from the data set of the IES case study reported in [4]. This can lead to conflicts with the irradiation data since the data sets are for different years. Electricity demand data were provided by all three participating firms. This data was measured quarter-hourly by smart-metering systems. For the three firms, different time spans of data were obtained, but always accounting for one year. Two firms revealed their energy demands for the year 2021, the other for the year 2020. The data from firm Z of the year 2020 was multiplied by 1.2 in order to account for the anticipated growth of the firms' energy demands over the next two years. For confidentiality reasons data and participants are not disclosed (and only the aggregated data was provided).

Heating demand data are only available for two of the firms since the last participant supplies all relevant heating by waste heat from electric process heating. For the other two firms, the heat demand is again supplied for the years 2020 and 2021. Feed-in tariffs were taken from the Federal Network Agency (*Bundesnetzagentur*) for the year 2022 [10].

Electricity prices were provided by the participating firms and matched with the respective demands. Gas prices, in contrast, were only available for one participant and assumed to be the same for the other firm. The CO_2 emission factors for gas and electricity were taken from [5]. The rooftop area for one of the firms was calculated by the application PV Sol premium 2022, while the areas for the other firms deviated from the best-case scenario, which would be the usage of the maximal area available at the industrial site.

Techno-economic data for the components used in the study is from different sources, but were mostly adopted from the IES case study [4].

The data comes in large quantities. Since quarter-hourly data for a year is analyzed, one is looking at $4 * 24 * 365 = 35{,}040$ data points. To reduce the data to fewer, more representative points time series aggregation (TSA) is used before the optimization. The TSA is following the approach introduced in [11]. This results in four typical days, each representing the days most similar to it. The four days themselves are broken down from 96 time steps of a quarter-hour to four representative time steps in a day, as seen in Fig. 2. This reduces the data to 16 time steps a year, plus the maximum demands for heat and electricity.

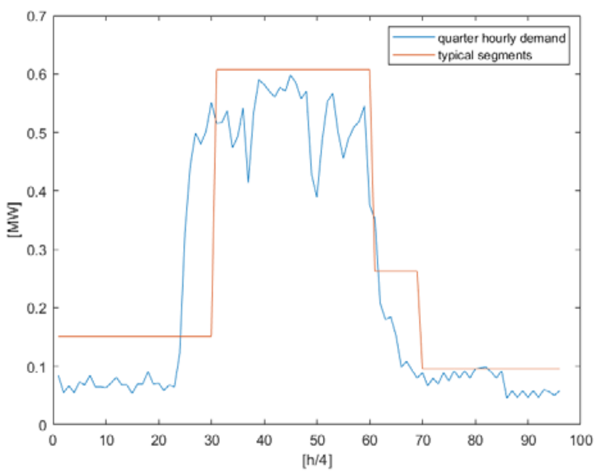


Fig. 2 Linearization of a daily, quarter-hourly electricity load curve to four typical load segments

4. CASE STUDY

The case study participants are firms I, K and Z, with Z producing machines primarily for the use in the production of plastic products and K and I being firms producing plastic products. Firm Z is working one dayshift, electricity is mostly used during the dayshift (Fig. 2), heating is realized through floor heating and the firm only produces during weekdays, while K and I are running continuously (24/7 operation). Firm K´s production is strongly reliant on extrusion. Extrusion is a process in the production of plastic products requiring large amounts of heat, which is usually generated through electricity. The extrusion requires large amounts of heat year-round, which is generated through electricity. This leads to constant electricity demand. Most production buildings are old and poorly insulated. Heating is supplied by radiators, needing high inlet temperatures. Firm I is producing non-woven fabrics. It is also relying on extrusion heavily. The extrusion is also powered by electricity and production is continuous throughout the year. Relevant heating demands are provided solely through waste heat from the production machines. Therefore, only electricity demand exists. The sum of the electricity demands of firms K and I is almost identical and for each is about 150 times the amount demanded by firm Z.

The firms are paying different prices for their electricity, which is taken into account through three different price scenarios. These scenarios are run for the different setups of operation, with those being the BAU scenario, each firm´s sole operation scenario and the community scenario. The BAU scenario for each firm and for community use are run to establish a baseline. The BAU scenario allows only for the usage of the power and gas grids and a boiler for heating. It is run at the price firm Z is paying now (P_Z), the price the utility operator is charging (P_U) and at market prices (P_M) to be able to compare the results with community usage later. The results show the annual costs and reduction of the GWI when firms keep running their operations as before. The added up individual BAU scenarios compared to the joint BAU scenario takes the energy-sharing (synergy) effect into account. To determine how the different users benefit from the energy system optimization, the optimization is run for each firm separately. Comparing the results to the BAU scenario quantifies the benefits individually. Thereafter, the community scenario is run at the operator and market price. The comparison of these scenarios with the community BAU scenario shows the effect of integrating renewables collectively. For all scenarios, the GWI-reduction is compared and measured against the economic benefits.

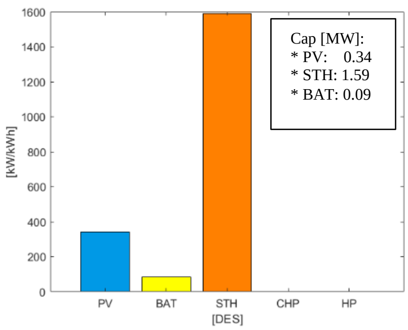
Overall, the optimization is done for the scenarios BAU, Z, K, I, C for the different electricity prices P_m, P_u and P_z. The results show that some of the effects are strongly compromised by the rooftop capacity restrictions; therefore, two extra simulations (scenarios 19 and 20) were run without any rooftop capacity restrictions.

When collecting the data, the authors also learned about some of the case study participants´ motivations. Besides the shared goal of reducing the negative environmental impact of their energy supplies, objectives were quite different. Firm Z was most interested in achieving the highest degree of self-sufficiency possible. Due to the recent energy price rises the company wished to meet as much of its energy needs by self-supply, thus reducing its reliance on the utility grid and the high tariffs charged by the grid operators. Self-supply would, so the expectation, help to reduce uncertainty about future energy costs and increase the company's planning security. Firm K tied its energy supply goals to the corporate goal of reducing its greenhouse gas emissions by 30% by 2030. Its goal was to reduce emissions as much as possible without losing money on the investment. Lastly, firm C was mostly interested in cost minimization.

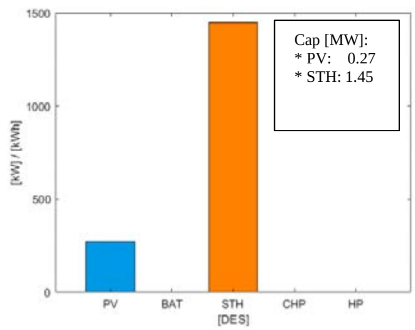
A more detailed overview of the optimization model, the data used in the optimization and the case study participants can be found in [12].

Table 1. Optimization results for the nine main scenarios considered

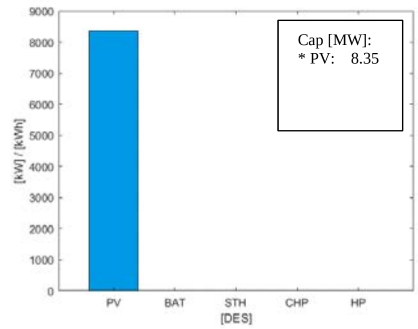
Criterium	Unit	Z_Pz	Z_Pm	Z_Pu	K_Pm	K_Pu	I_Pm	I_Pu	C_Pm	C_Pu
NPV	€	431.87	negative NPV	222.69	3,637.79	17,991.95	3,308.55	13,544.67	4,165.81	22,310.38
GWI	ktCO_2-eq/a	-116.98	X	-57.67	14,589.16	14,531.00	12,905.78	12,905.78	32,842.01	32,801.88
ROI	%	0.2230	X	0.2236	0.1675	0.4162	0.1645	0.3572	0.1676	0.4759
Amortisartion	a	4.48	X	4.47	5.97	2.40	6.08	2.79	5.97	2.10



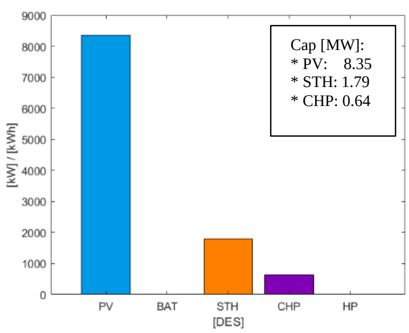
(a) ZP_z scenario



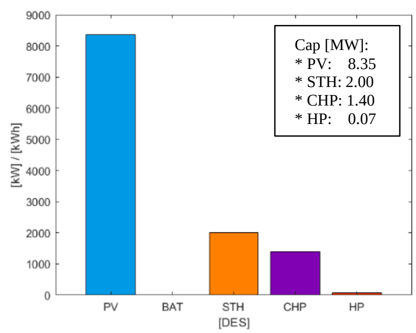
(b) ZP_u scenario



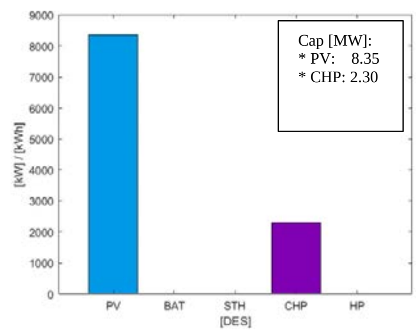
(c) IP_m and IP_u scenarios



(d) KP_m scenario



(e) KP_u scenario



(f) CP_m and CP_u scenarios

Fig. 3 Optimal capacities of DES installed for the different scenarios (except for: Z_{Pm} where the NPV is neg.; I_{Pm} and I_{Pu} which are shown jointly, as they only differ w.r.t. the hot water storage unit; C_{Pu} yields the same optimal capacity as C_{Pm})

5. RESULTS

This section reports on the findings from the optimizations conducted. The integration of DER in the existing energy systems always resulted in positive economic (NPV, ROI, payback time) and ecological (GWI) effects. Even for low energy prices (P_m), integration was beneficial. One exception was the ZP_m scenario, where low prices were assumed for inconsistent demands, leading to a negative NPV. In all other scenarios, the integration yielded returns on investment (ROI) between 12.46 and 47.59%. Payback times ranged between 2.4 and 7.9 years. Economically all optimizations resulted in a decrease in the GWI, for firm Z the GWI value even turned negative, due to the credit given for the renewable electricity that is fed into the grid (net metering).

The resulting outcomes of solving the objective functions and the respective sizing of the components can be seen in Table 1 and Fig. 3, respectively.

The sizing of the installed DER depends highly on the prices charged for power taken from the grid. This can be seen either when looking at the amount of PV installed for firm Z in the ZP_z and ZP_u scenarios or from the CHP amounts installed for the KP_m and KP_u scenarios. For firm Z, the installed PV rose by 26.2% when switching from the price of the utility provider to the higher price Z is paying in the ZP_z scenario (Fig. 3(a), (b)). Note the different scales in Fig. 3. CHP is affected by the different prices because its produced electricity is competing with the electricity taken from the grid. Therefore, higher prices charged make bigger CHP capacities profitable. For the two scenarios, the switching from the market price to the utility price led to an increase in CHP capacity of 118.75% (Fig. 3 (d) and (e)). To make use of the surplus heat additional heat storage capacity was installed as well.

The amount of PV installed in the KP_u, IP_u and community scenarios gave no evidence on the influence of the electricity prices on the installed DES capacities since the maximal capacity of PV was installed each time.

For the case study, CHP installation usually dominated HP installation. This has two reasons. To explain the first reason the price of electricity should be compared to the gas price and related to the HP´s COP. The COP of the HP cannot exceed 4 and the HP transforms electricity into heat energy. The market electricity price is about two times the gas price. For this scenario, HP use could be feasible. For the other scenarios, the relation between the electricity and gas price is larger than a factor of 4. Whenever this is the case using the HP with electricity from the grid is not feasible anymore. The alternative would be using electricity produced in the DES but, since demands were consistently high and direct consumption was favored, this is rarely the case. The second reason for not installing HP capacity was its parametrization. The HP´s flow temperature was set to 70° C. However, HPs are most effective (and thus energy-efficient) at low flow temperatures. This as well made the usage of the technology less favorable.

Battery storage was only used in the ZP_z scenario (Fig. 3(a)). Here P2P trading was not allowed, and the demand fluctuated over a day's time span. The battery was able to optimize PV usage for this scenario. In the other scenarios, the demand was always high when PV was available; therefore, all electricity produced could be consumed directly and did not need any energy storage.

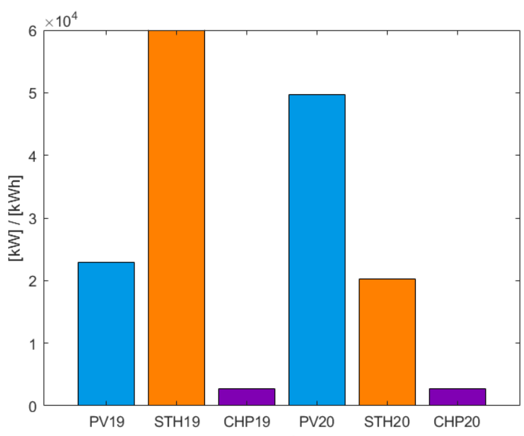


Fig. 4 Optimal DES capacities, scenarios 19 and 20

The usage of P2P trading in the community scenarios yielded both, economic and ecological benefits. However, the effects were restricted by the maximal rooftop area available for PV installation. The effects can be seen in the scenarios 19 and 20 (Fig. 4), where PV restrictions were disregarded. The NPV at market prices was more than 4.5 times as high as in the CP_m scenario and a GWI reduction of 12,769 or 19,091 ktCO_2-eq/a was possible compared to the CP_m scenario.

Lastly, the effect of P2P trading on installation size can be seen when comparing the Z scenarios with the energy community scenarios. When firm Z integrates PV itself, the full rooftop capacity is not used for any scenario. In contrast to that, rooftop capacity of Z is always used to the maximum when cooperating with the other firms.

6. DISCUSSION

The limitations of the case study are that unrestricted P2P trading is assumed, uncertainties in electricity and technology prices are ignored, and changes in the future energy mix of the utility grid are uncertain. Note that the price development is particularly important due to its double impact on the simulation: it affects the economic benefits but also influences the amount of DES installed. Furthermore, the case study is limited to firms with only gas and electricity (as power input and cooling is not included). However, this limitation can easily be overcome by making minor changes to the underlying optimization model.

Despite its limitations, the case study results allow to derive policy implications for future users and legislators concerned with REs. One big limitation for integrating DES is the restricted possibility of using energy generation technologies. Even though demands were high and optimization without limits recommended high, capacities of PV, the area available for the installation of PV was very limited.

Interviewing the CEOs of the firms investigated confirmed that the willingness to invest in DES is high and firms are searching for ways to become carbon-neutral. Legislators could support the firms' ambitions of becoming more sustainable by allowing for the installation of PV at other locations and the virtual usage of the electricity generated for self-consumption. Another possibility would be the lifting of limitations related to wind power generation, enabling the installation of wind turbines in the proximity of industrial areas. Another important barrier to integration of more DES was the lack of information. During the research for the case study, authors became aware that the information available on the profitability and sizing of DES in the industry is still scarce.

Executives did not know about the economic factors of DES in the industry, and experts, including those from PV-installation companies, even with exact demand profiles, were unable to calculate the optimal size of PV installations on the firms' rooftops right away, leaving interested energy-intensive firms with information gaps and hindering the spread of DES in industry.

7. CONCLUSIONS

We find that the integration of DES has positive effects on all firms and for all scenarios. The ROI was never lower than 12% and payback periods often shorter than four years. The GWI reduction was around 65% in the energy community scenario. For individual firms, a negative GWI was possible – as large amounts of surplus electricity are fed into the grid, and because the surplus is accredited for as GWI credits – while still yielding an ROI of 22%.

The optimization was done for three different firms. Firm Z was relatively small, whereas firm I had no heat demand. DES integration proved feasible for all three firms. Economic and GWI benefits were high for the firm having electricity demand only (NPV: 13,545 k€ / GWI reduction: 5,691 kt$CO_{2\text{-eq}}$/a); it increased for firms having heat demand (NPV: 17,992 k€ / GWI reduction: 6,793 kt$CO_{2\text{-eq}}$/a) and increased further when P2P trading was possible (NPV: 22,310 k€ / GWI reduction: 7,293 kt$CO_{2\text{-eq}}$/a). Technically speaking, since the optimization is based on a firm´s demand, optimization results are different for firm and optimization must be run individually. When simulation is done for other firms in other scenarios, the input parametrization must be checked carefully, since uncertainty is high regarding demands, prices, tariffs, weather, and their respective future development.

Since no restrictions were assumed for energy sharing, future works could implement different P2P setups, fitted to the particular conditions. This could also be used to evaluate the effects of different P2P trading mechanisms on the optimal design and operation configurations. Also, subsequent research could implement other DES i.e.: electrolysis, storage and fuel cells for hydrogen. Lastly, improvements in the TSA could allow for global optimization.

There is scope for further research. For instance, different P2P setups could be investigated to model real world market situations; an improved TSA could be conducted to identify also globally optimal solutions; and the implementation of other DES, such as electrolyzers, hydrogen storage and fuel cells seem a fruitful expansion of the current research and scope of the analysis.

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