2018 53rd International Universities Power Engineering Conference (UPEC), Sept. 2018, Glasgow, Schottland

District Energy System Optimisation and Communication: A Two-Level Approach

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***Abstract*—This article presents a two-level optimisation approach for the management of controllable and distributed converters with storage systems across different energy sectors. It aims at the reduction of electrical peak load and at the economical optimisation of the electrical energy exchange with the grid, based on a dynamic external incentive, e.g. through dynamic energy price tariffs. By means of a secure, standardised and lean communication with two different internal price signals, an optimal flexibility provision shall be achieved. The two-level optimisation approach consists of a centralised and several distributed decentralised entities. At the centralised level, the distributed flexibilities are invoked for optimal scheduling on the basis of an internal price algorithm for stimulating the decentralised entities. Based on that internal incentive and on the expected demands for electricity, heating and cooling, the decentralised optimisation algorithms provide optimal generation schedules for the energy converters. The suggested interaction between the central and decentral entities is successfully tested and the principle potential for peak shaving and the adaption to dynamic energy-related market prices could be demonstrated and compared to different energy management strategies such as the standard heat-led operation. Further, variations of the system parameters such as load shifting potential, installed capacity and system diversification are evaluated against cost saving potential for the energy supply and overall system performance.**

Keywords—decentralised systems, distributed optimisation, distributed simulation, energy management, flexibility, internal price signals, open standard communication protocol, peak shaving

I. INTRODUCTION

Owing to the increasingly volatile electricity production due to weather dependent photovoltaics and wind turbines, new requirements for the energy management of districts in terms of interacting with the grid in a flexible manner will arise. Load shifting is one imminent method not only for securing the electricity supply at a cost-effective manner but also to balance generation and demand. Additionally, the use of intersectoral flexibility i.e. coupling electricity, heat and cooling resources can complementary contribute to the efficient integration of renewables.

Depending on climatic conditions and industrial processes, often a high portion of total end energy consumption is due to space heating as well as cooling demands, which is mostly fulfilled by peak load boilers, CHP units and electrically driven cooling plants. Generally, the operation of these plants is based on the energetic state of the storage systems i.e. turning the plants on when the thermal storage is empty and vice versa. On the electricity side, in addition to static energy taxes and reallocation charges there are two directly influenceable parts of the electricity supply costs, i.e. grid charges, which depend on the peak load during the year and of dynamic energy charges per kilowatt-hours of energy consumed. By coupling thermal and electrical sectors, the flexibility provided by the thermal storage systems can be used to shift the electrical load in times of lower electricity prices as well as cutting down the peak load to reduce associated grid charges.

In [1], roles of integration for energy storage systems, electric vehicles and demand side management (DSM) have been briefly reviewed and the need of the intelligent management of energy storage systems is stated. The potential analysis and comparison of the different load management mechanisms such as direct load control, DSM, use of batteries and electrical vehicles as well as combined cooling, heating and power (CCHP) is outlined in [2, 3]. The PowerMatcher technology uses dynamic prices as a control signal for the distributed energy resources (DER). The load shifting potential is successfully demonstrated, and it is further argued that the true integration of DER will result in full utilisation of the flexibility potential of DER's [4]. A similarly distributed

This article was created within the project ENsource (http://www.ensource.de/) which is funded by the Ministry of Science, Research and the Arts of the State of Baden-Wuerttemberg and the European Regional Development Fund (EFRE). Support code: FEIH_ZAFH_562822.

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optimisation approach based on the principle of internal incentive signals or referred to therein as shadow prices is presented in [5] and shows significant advantages in terms of scalability and data integrity over a central optimisation. A survey of demand response potentials and its benefits in smart grids are presented in [6]. This article underlines the importance of smart meters, home energy controllers, energy management and communication systems for market efficiency as well as overall peak load reduction. A bi-level aggregator-utility optimisation model with a spot electricity market is proposed in [7], which considers a direct load control mechanism for DSM with three different types of controllable loads and a high penetration of wind energy. Load frequency control can be effectively carried out with the help of load aggregation consisting of a large number of plug-in hybrid vehicles and flexible household appliances without stressing the underlying physical network or violation of comfort constraints [8]. The principle work in energy management of districts with a number of controllable consumers focuses on DSM using sophisticated optimisation methods, as extensively summarised in [9]. Further, a lot of work has been done in the area of agent based machine communication, especially in the field of automation in production, refer to [10]. Therein they formulated a generic agent representation within the powerful meta model of the open communication standard OPC Unified Architecture (OPC UA) to facilitate handling of complex production systems comparable to the requirements of energy management systems.

The present article combines the efforts in optimisation of decentralised entities and communication between different applications for a district energy management system by using the open and secure communication standard OPC UA with the objective of reducing the peak load and overall electricity supply costs.

II. SYSTEM DESCRIPTION

A. Overview

Fig. 1 shows the proposed structure of the two-level energy management system for distributed energy systems as it can be applied in commercial, industrial and residential sectors. In total there are three different layers: The energy market layer for the physical and economical external interactions and the two inner energy management layers with the central optimisation on the aggregating district level and the decentral entities optimising their local demand. In order to grant a high level of autonomy and control to the smart decentralised subsystems, namely buildings with smart CHP units, heat pumps, cooling plants, etc. the proposed approach utilises energy market prices for electricity (1) to generate internal price signals for a given prediction horizon, e.g. for the upcoming 24 hours (2) as the basis for the decentralised units to optimise their operations. Considering the subsystems properties and the predicted energy demands (3), the subsystems derive optimised generation and consumption schedules. These schedules and additional information on flexibility ranges (4) are communicated to the central optimisation unit, which in turn examines whether the overall optimisation goals are achieved. Those goals include peak shaving to a given power limit in order to reduce grid charges and to shift energy consumption in times of lower energy prices. Iteration of this process creates a virtual internal market. As a result, the inherent potential for flexibility can be raised and made available to the external environment respectively to the grid and an external energy market (5).

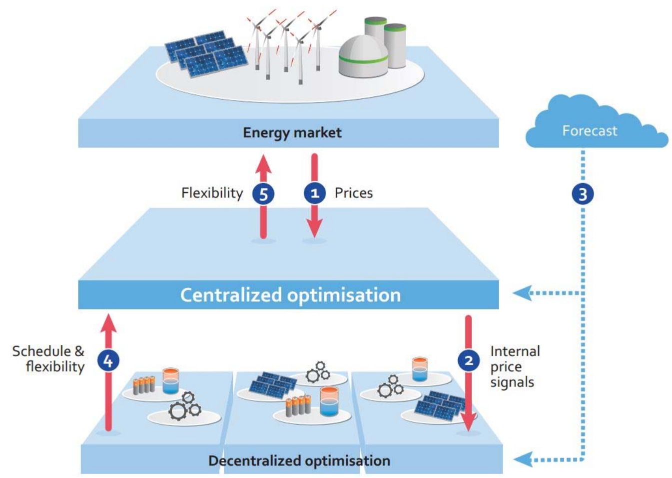

Fig. 1: Two-level approach for energy system optimisation: interaction and communication between the different layers

B. Receding Horizon

The described iteration process pictures the energy management methodology for the upcoming 24 hours, only. In order to cover a longer time period, like a week, a month or a year, the described iteration process is repeated in frequent time steps in analogy to the receding horizon control [11, 12]. As time progresses, the optimisation is repeated continuously after a certain time interval, each time covering a part of the previous prediction horizon and new time steps that have not been considered yet. Thus, the first optimisation leads to an optimised schedule taking into account all the information of the first prediction horizon. During this schedule is executed, after a certain time gap of i.e. 8 hours (optimisation cycle) according to Fig. 2, the next optimisation sample is started, considering the obtained operating status such as state of charge (SOC), cumulated operational time, etc. and reaching further into the future.

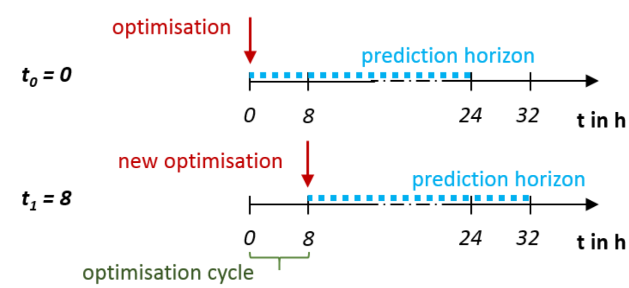

Fig. 2: Receding horizon: The optimisation sequence is repeated periodically reaching further into the future

C. Depicted system components

In order to investigate the system dynamics of the proposed approach, an exemplary energy system is defined. It consists of decentralised subsystems, i.e. typical commercial buildings with intersectoral energy converters and storage systems, as listed in Tab. 1. In addition to the specific non-controllable electrical load profiles, different types of synthetic heating and cooling load profiles are assumed for each type of building. Further three types of energy converters with a significant impact on the overall electrical load profile are assumed, i.e. combined heat and power units (CHP), heat pumps and cooling units each with an individual thermal energy storage (TES).

Tab. 1: Assumed energy system and associated subunits

Name	System description
	Building types | considered load profiles
B1	data center | (el., cool.)
B2	office with laboratory | (el., cool., heat.)
B3	office | (el., heat.)
B4	test facility | (el., cool., heat.)
B5	office + air dehumidification | (el., cool., heat.)
B6	workshop | (el., heat.)
B7	factory | (el., heat.)
	Decentral energy resource type
DER1	CHP unit + TES (4 units with 1534 kW_{el} total)
DER2	heat pump + TES (2 units with 543 kW_{el} total)
DER3	cooling unit + TES (4 units with 520 kW_{el} total)

III. OPTIMISATION

A. Centralised optimisation

The centralised optimisation algorithm aims at a cost optimised overall schedule for the electricity supply, while heating and cooling demands are addressed individually by the decentral entities. Approaching this goal there are two main objectives: maintaining the given power limit due to grid charges and shifting the electricity consumption in times of low energy prices (incited by dynamic external energy tariffs). The main idea is to use the aggregated sum of flexibilities of the different entities to enhance the overall benefit. Therefore, the decentral entities communicate, based on given price signals, for every interval their desired schedule together with their flexibility or in more precisely their possible adaption for minimising or maximising their power output or input (Fig. 3). These result into a cumulated schedule for all entities with an overall flexibility belt. Together with the power limit, external dynamic energy tariffs and the previously calculated internal price signals they serve as basis for the centralised algorithm to deduce new internal price signals as an incentive for schedule adjustments (Fig. 4). The algorithm works with two different price signals for generation and consumption. First the internal generation prices are calculated and passed on to the decentral entities. Incorporating the corresponding decentral response, the internal consumption prices are deduced and communicated. The exchange of schedules and price signals is iterated till the optimisation goal is reached. In this way the heuristic of the algorithm works comparable to a PI controller with the different prices as actuating variables. Due to the rather discrete behaviour for a limited number of decentral entities the two-price algorithm is chosen over a one-price algorithm, allowing for a smoother balancing of individual units. Moving from the coarse to the fine, for the presented example the generation units get optimised before the consumption units because of their higher overall capacity and their longer minimal running and rest time.

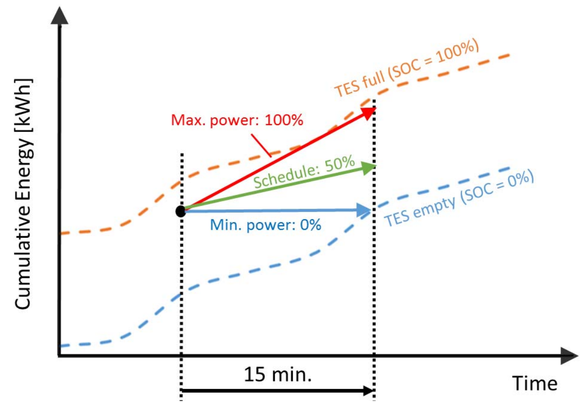

Fig. 3: The decentral entities communicate their desired schedule together with their flexibility to adapt their power output or input

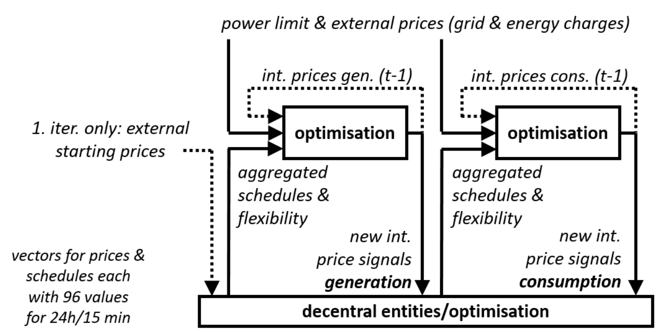

Fig. 4: The centralised optimisation generates internal price signals based on the given power limit, external energy charges, previously calculated price signals as well as the aggregated schedules with the flexibility information of the decentral entities

B. Decentralised optimisation

Based on the operational temperatures and size of the thermal energy storage, the thermal flexibility provided by the TES can be exploited in order to schedule the operation of the associated energy converter. The suggested graduated energy management concept allows the implementation of various decentralised optimisation methods and only requires a standardised input/output interface. Although in this study two optimisation methods of stochastic-heuristics and linear programming for scheduling decentralised entities are used, the basic approach for scheduling the decentralised entities remains the same. Fig. 5 shows the basic optimisation principle using the example of a CHP unit. Based on the building specific thermal demands (Tab. 1) two limiting curves of cumulated lower (storage empty) and upper heating demands (storage full) are calculated, which act as boundaries for the generation schedule, as shown in the upper subplot of Fig. 5. The generation schedule fulfils the thermal demand with minimised costs based on the variable internal electricity prices. The depicted example is computed using stochastic-heuristics for a modulated CHP unit. Thus the CHP unit runs at full power during high internal electricity prices and modulates itself according to the lower prices. For electrical consumers such as heat pumps and cooling plants the same optimisation principal applies but resulting in a vice versa behaviour. Additional system parameters such as minimum operational times, minimum rest times are also taken into account. Other decentral entities like cooling plants are optimised by a linear programming method. Further details of rules for the generation of optimal schedules according to the used optimisation methods can be found in [13, 14].

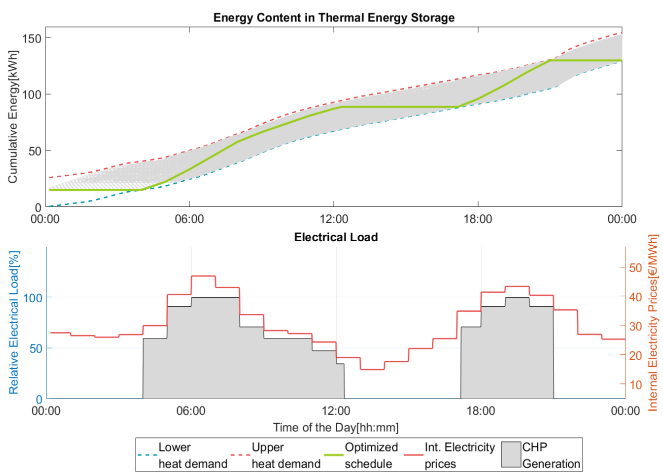

Fig. 5: Basic decentralised optimisation principle using the example of a modulated CHP unit

IV. Communication

In order to demonstrate the proposed two-level optimisation approach, a simulation environment has been developed, which depicts the aforementioned optimisation procedure together with a standardised communication concept, refer to Fig. 6. Since the proposed approach preferably addresses energy systems with energy converters, storages and buildings that are distributed within building districts, possibly even across multiple actors, the structure of the simulation environment has been adapted to this case. Therefore, each research site involved in the project represents a respective entity or several entities each of the same type and communicates via internet (TCP/IP) and the open communication standard OPC UA.

Based on the typical client and server architecture of OPC UA, the client entities access the address space of the server via the basic communication services, e.g. read, write, connect, browse, etc. Within the UA address space, uniform object nodes are defined for the central and decentral entities, refer to Tab. 2. While on the UA client side each entity is represented by a python interface to OPC UA, the UA server is located on an industrial PLC. The used optimisation algorithms have been developed with software packages in python and MATLAB.

Tab. 2: Parameters of the communication and simulation process

Name	Description
	Central Entity
sim period	simulation period, here: one week
sim step	simulation step, here: 15 min
plan. horizon	prediction horizon of each calculation step, here: 24 h
opt cycle	cycle time between two optimisation steps, here: 8 h
flag abort opt	status variable if peak load minimisation is reached or available time budget elapsed
	Decentral Entity
name	name of decentral entity, e.g. CHP1
best iteration	number of best schedule within a optimisation horizon
flag	status variable to handle pricing and scheduling interaction between central and decentral entities
price signal	price trajectory
schedule	optimised electrical consumption/generation schedule trajectory
flex bottom	lowest possible electrical consumption/generation trajectory
flex up	highest possible electrical consumption/generation trajectory

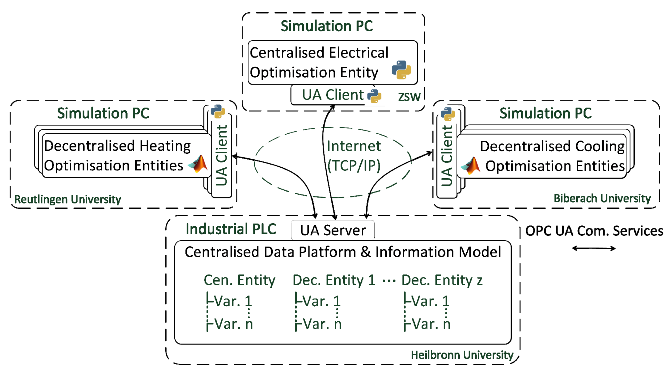

Fig. 6: Simulation environment and communication concept

V. Simulation

A. Simulation parameters & Input data

In order to show the feasibility of the previous described two-level approach and to deduce general trends regarding its performance, different scenarios have been simulated. Simulation parameters such as the simulation period, prediction horizon, simulation step size and optimisation cycle are used as shown in Tab. 2. Furthermore, the introduced buildings are represented by the corresponding load profiles for electricity, heating and cooling in an exemplary transition period, presuming an optimal forecast for the demand. Refer to Fig. 7 depicting the aggregated load profiles as well as the assumed dynamic energy price trajectory for the simulated week. A total number of ten decentral entities are assigned to the assumed load profiles (refer to Tab. 1) for the standard scenarios, namely four cooling units, two heat pumps and four CHP units (whereof two can be modulated). The peak limit is set to the theoretical minimum of 4848 kW.

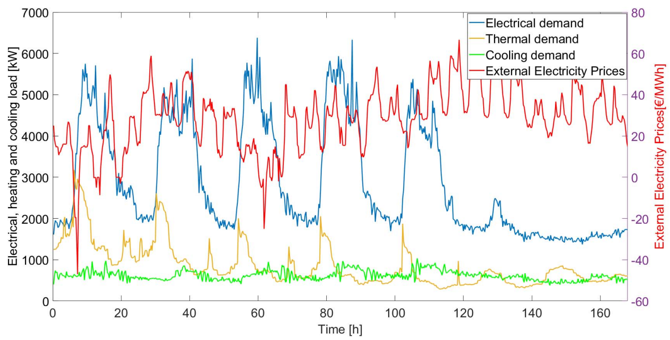

Fig. 7: Assumed synthetic input data: aggregated electrical, heating and cooling load profiles and dynamic external electricity price signal

B. Scenarios

The different scenarios, as listed in Tab. 3, are meant to roughly examine the effect of the two-price algorithm within the two-level approach compared to other management strategies (reference scenarios Ref 1-3). Further scenarios reflect the influence on the performance (costs and peak load) when diversifying different parameters like the energy shift potential (A), controllable electrical system power (B) and finally the number and diversity of the different entities (C). For C1 the original decentral heating entities and profiles are split into two but both with equivilant parameters and the same generation type; in C2 the latter is also varied.

Tab. 3: Scenario description: the shift potential in hours is defined as the timespan that can be covered by a full TES at maximum thermal peak load without thermal generation; installed capacities of the thermal energy converters are also oriented on the value of the thermal peak load

Scenario	decentral entities	shift potential	Inst. cap.	Energy management strategy
Ref-1	10	4h	x1	heat-led, 2 point controller
Ref-2	10	4h	x1	price-led, external market price
Ref-3	10	4h	x1	algorithm with one internal price
A1/ Ref-4	10	4h	x1	algorithm with two internal prices (2-P)
A2	10	**8h**	x1	2-P
A3	10	**2h**	x1	2-P
A4	10	**1h**	x1	2-P
B1	10	4h	**x1.3**	2-P
C1	**16**	4h	x1	2-P
C2	**16 + extra diversity**	4h	x1	2-P

VI. Results

The feasibility of the two-level approach is confirmed against the pure fulfilment of the thermal demands (heating and cooling) of the buildings. Further, the system structure is built in a way that the communication between the two levels is standardised and can be further expanded to well over 100 decentral entities. Additionally, the secure internet capability of OPC UA enables stable communication even outside of local communication networks, which was successfully tested.

Fig. 8 shows the presented methodology for peak shaving to the given power limit, shown by the horizontal grey line in the upper subplot. In addition, the upper subplot shows the resulting total electrical load profile and the associated flexibility for adapting this first schedule, which resulted from the directly forwarded external energy price trajectory of the first optimisation iteration. As it can be seen therein, the electrical load often exceeds the given theoretical limit of 4848 kW and hence at these times the internal electricity prices are adapted for the following iterations (third subplot). As a consequence of the proposed interaction via the adjusted incentives and proposed schedules, the peak load is reduced below the given limit after the second optimisation iteration (second subplot). This results from the shifted schedules of the subsystems for the controllable electricity generation and consumption (fourth subplot).

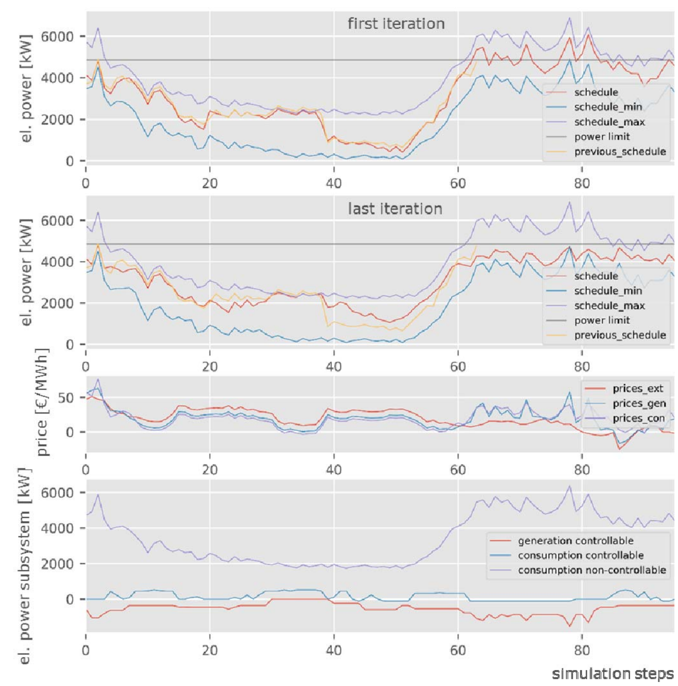

Fig. 8: First iteration: The schedule exceeds the given power limit; last iteration: Through the incited shift in consumption and generation the given power limit can be met

The performance of the different scenarios is evaluated with reference to the heat-led operation scenario (Tab. 4, Ref-1) as well as the standard two-price algorithm scenario (A1/Ref-4) focusing respectively on the achieved reduction for the maximum peak load and the associated electricity charges. The assumed grid charges are 111,49 €/(kW a) and 0,8 ct/kWh and the dynamic energy prices for the energy charges are shown in Fig. 7. Comparing the different energy management strategies, it stands out that the strategies with individually optimised decentral entities (Ref 1 & 2) lead to a much higher overall peak load than the centrally optimised scenarios (Ref 3, 4 & following). Due to the grid charges, this advantage also influences the total energy supply costs; even for the price-led scenario (Ref 2), the low energy charges can barely compensate for the higher grid charges. In the end the two-level approach is beneficial in contrast to a simple decentralised and not interrelated optimisation strategy. In this example the one and two-price algorithm show similar performance, even though the two-price algorithm shows slightly better results. Looking at different storage capacities (A1-4), the results underline the assumption, that a higher shifting potential enables an enhanced performance. Additionally, scenario B1 shows that the installed and controllable power capacity of the system directly effects the results and allows to reduce the electrical peak load at higher power output even more. A mere rise in number of the decentral entities (C1) does not lead to better results, however paired with an increase in diversity (C2) an improvement of the situation referring to the power limit can be achieved.

Tab. 4: Results for the simulation period of one week

Scenario	**peak load** [kW]	**grid charges** [€]	**energy charges** [€]	**energy supply costs & cost advantage** [€ / %]
Ref-1	6526	17 581	11 975	29 556 (0 %)
Ref-2	6814	18 158	10 991	29 149 (1.4 %)
Ref-3	5034	14 361	11 328	25 689 (15.1%)
A1/ Ref-4	5034	14 360	11 223	25 583 (15.5 %)
A2	4848	13 931	11 335	25 265 (17.0 %)
A3	5067	14 441	11 223	25 674 (15.1 %)
A4	5473	15 308	11 423	26 731 (10.6%)
B1	4829	13 935	11 356	25 290 (16.9 %)
C1	5034	14 360	11 223	25 583 (15.5 %)
C2	5015	14 542	12 106	26 648 (10.9 %)

VII. Conclusion

Compared to a centralised optimisation the proposed two-level approach and its standardised interaction offers advantages in terms of scalability and reduction of complexity due to the lean, secure and internet-enabled communication concept. In order to verify the developed algorithms, a simulation framework has been implemented by means of different simulation packages for centralised and decentralised optimisations each running on different hardware at the respective research sites. Using the open communication standard OPC UA combined with the developed methodology, opens up further potential for investigations such as handling of connection interruptions, hardware-in-the-loop simulations and further system automation, e.g. to deal with dynamically changeable system structures in an automated and smart manner.

Considering a limited period of one week, the simulation results of the two-level optimisation approach showed that coordination on a centralised level can significantly reduce the total electrical energy supply cost even in the presence of smart subsystems, which are each running their own energy management system. Market price driven isolated decentralised optimisation methods can achieve maximum savings in terms of energy-related electricity tariffs compared to purely heat-driven systems – at the risk of higher peak load. Thus, only the overall coordination leads to the reduction of the relevant peak load and associated costs while also generating benefits from energy related savings. Further potential for cost reduction of consumed energy is observed by increasing load shifting potential by means of increased thermal storage capacity. However, a more detailed analysis is necessary to evaluate which storage size is beneficial especially when looking at the associated higher investment costs. A higher installed capacity of the controllable power units allows for even further reduction in peak load. An increase in number of the subsystem can show the same effect but only when combined with a rise in diversity to allow for the subsystems to react individually to given price signals. Assuming an appropriate tariff structure for flexibility, the approach could also be suitable for a grid supportive operation.

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