Decentralized Resource Allocation and Load Scheduling for Multi-Commodity Smart Energy Systems

Niels Blaauwbroek, Student Member, IEEE, Phuong H. Nguyen, Member, IEEE, Mente J. Konsman, Huaizhou Shi, Student Member, IEEE, René (I. G.) Kamphuis, Member, IEEE, and Wil L. Kling, Senior Member, IEEE

Abstract—Due to the expected growth in district heating systems in combination with the development of hybrid energy appliances such as heat pumps and micro-combined heat and power installations, new opportunities arise for the management of multi-commodity energy systems, including electricity, heat and gas. The possibility to ‘convert’ forms of energy using hybrid energy appliances and exploiting flexibility from local production and consumption, can improve the systems’ efficiency significantly. This paper extends existing work with a decentralized version of a multi-commodity smart energy management system, in order to deal with flexibility and scalability. The system incorporates both heat and electricity and integrates various types of flexible appliances as well as hybrid energy appliances. To optimally allocate the available resources and its flexibility, the developed multi-agent system aims to perform optimal supply and demand matching of the local resources and flexible appliances, as well as to flatten the net remaining exchange over time. The proposed method is applied to a test case, where simulation results confirm that the decentralized approach leads to a scalable solution for the management of the multi-commodity smart energy system and performs similar to the centralized approach.

Index Terms—Combined heat and power; demand-side management; distributed algorithms; heat pump; multi-agent systems; multi-commodity; smart energy systems;

I. INTRODUCTION

In Europe and many other places of the world, a major part of energy consumption is from thermal demand. As the share of district heating is expected to grow drastically in the future, improvements in energy efficiency in thermal installations can be highly profitable [1]. The introduction of hybrid energy appliances such as heat pumps (HP) and combined heat and power (CHP) installations results in the ability to ‘convert’ electricity to heat respectively cogeneration of energy forms, improving the overall efficiency. With the development of smart energy systems by incorporating information and communication technologies (ICT), local energy resources and the flexibility offered by the various appliances can be exploited to optimize local energy consumption and production. By combining the electricity grid with the (district) heating system in a single multi-commodity smart energy system (MC-SES), opportunities arise to improve on efficiency, reliability and sustainability of the whole energy system [2]. Demand-side management (DSM) and demand response (DR) programs can be deployed in the MC-SES to pursue various kinds of objectives, like optimizing energy costs, performing supply and demand matching (SDM) and peak demand shaving or maximizing the usage of local renewable energy sources.

However, the development of smart energy systems is challenged by different aspects. Firstly, it needs to be decided on the management approach of the MC-SES to be either centralized or decentralized [3]. In the centralized approach, the management strategy is carried out by a single entity, controlling all the energy resources and flexible appliances within the system. The decentralized approach makes use of distributed intelligence technology to carry out the management objective without relying on centralized decision making infrastructure. Secondly, flexibility offered by appliances can exhibit several types, such as postponing or advancing a certain consumption and buffering or storing energy. The smart energy system must be able to deal with all of those types of flexibility. Lastly, the management strategy can be developed for performing instantaneous control as well as time horizon control, taking into account a longer period of time. Since the flexibility offered by appliances on their consumption and production often is known in advance, it enables time horizon rather than instantaneous scheduling is likely to result in more optimal schedules, taking more advantage of the flexibility offered by the appliances.

Although smart energy systems have been studied thoroughly [4], they have mostly addressed only one single form of energy, optimizing either electrical or thermal energy. DSM and DR strategies to control the electricity consumption at the customer side have been proposed in many studies such as in [5] - [9]. An example of a decentralized DSM strategy with time horizon management is presented in [10], aiming at optimal charging of electric vehicles, but therefore only including a single type of flexibility. Also, the management of thermal energy systems has often been subjected to research as in [11] - [13]. The research presented in [14] focusses on an electrical heating installation together with flexible electrical...
loads. It incorporates extensive models of the home and heater properties, although it does not include the exchange of thermal energy among various thermal appliances in a thermal energy grid. In [15] both an electrical and thermal energy grid are included in a multi-commodity DSM system. However, the system is based on a market scheduling mechanism that performs instantaneous matching of the local supply and demand, rather than time horizon optimization.

In [16], a centralized management strategy of MC-SES has been presented, featuring time horizon optimization for both electrical and thermal energy. The optimal allocation and scheduling is capable of dealing with different types of flexible appliances, as well as multi-commodity appliances as HP and CHP. This paper aims to extend the research presented in [16] by establishing a decentralized version of the coordination mechanism for the MC-SES in order to manage the complexity and to deal with scalability. For this purpose, the decentralized approach will use distributed intelligence technology, also called a multi-agent system (MAS) to perform the optimization. For this purpose, the optimization will be split in small locally solvable optimization problems. The IEEE Power Engineering Society’s Intelligent System Subcommittee has published contributions [17] and [18] about the potential values of MAS for the power industry, as well as guidance and recommendations on how MAS can be designed and implemented in the power and energy sector.

The decentralized approach will embrace the same characteristics as the centralized version presented in [16], making intelligent decisions across the electrical and thermal commodities and using the possibility to convert between those forms of energy. Specific advantages of the proposed decentralized MC-SES are:

- The system can deal with the same types of flexible appliances as presented in [16], being buffer, time shifter, and uncontrolled appliances, together with multi-commodity appliances as HP and CHP. Therefore, the same constraints for each appliance are included.
- The system is able to perform time horizon optimizations with various kinds of objectives, including energy cost minimization, peak demand shaving and local supply and demand matching.
- The system features a fully decentralized decision making approach, of which the performances are verified and compared with the centralized approach using a practical test case.
- Due to the decentralized nature of the proposed method, the system is highly scalable and more adaptable for dealing with the different types of flexibility compared to the centralized optimization.

The remainder of the paper is organized as follows. Section II will give an overview of the MC-SES with the network model, (hybrid) energy appliances and the cost model. Thereafter, section III will present the decentralized optimization approach, of which the results are compared with the centralized approach of [16] using a test case in section IV. Finally, section V will elaborate on the conclusions and recommendations.

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Fig. 1. Architecture of a typical energy supply system with district heating.

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II. MULTI-COMMODITY SMART ENERGY SYSTEM

This section treats the representation of the MC-SES, electrical, thermal and hybrid energy appliances.

A. System model

In Fig. 1 an overview is given of the architecture of a typical MC-SES, comprising two forms of energy \( f \in \{e, h\} \), to be electrical energy \( e \) and thermal energy \( h \) (heat). Shown are both the distribution grid and the heat pipes for district heating. Various appliances including local renewable energy sources, storage units and (flexible) loads, like home and domestic appliances, are connected to both the LV grid and the district heating pipes. Throughout the paper, let \( \mathcal{A} \) denote the set of appliances that are participating in the MC-SES. Within the set of participating appliances \( \mathcal{A} \), there are two subsets of appliances \( \mathcal{A}_f \subseteq \mathcal{A} \) using energy from \( f \in \{e, h\} \), where \( \mathcal{A}_e \) is the set of electric appliances, and \( \mathcal{A}_h \) is the set of thermal appliances. In between the electricity grid and the district heating system two hybrid energy appliances are present, in which both electrical and thermal energy (as well as gas) are involved. The first one is a HP, which uses electrical energy to extract thermal energy from a thermal source like the ground and releases it to the thermal energy grid. The second one is a CHP installation, which produces both electrical as well as thermal energy by burning gas, also called co-generation. For the sets of appliances holds that \( \mathcal{A} = \mathcal{A}_e \cup \mathcal{A}_h \cup \{\text{HP, CHP}\} \).

B. Electrical and thermal appliances

Various types of (flexible) appliances have been defined, such as buffering appliances, time shifting appliances and uncontrolled appliances. They have been generalized in a so-called control space (CS) that is based on a conceptual energy flexibility framework as in [19]. In this CS, the flexibility that the appliance can offer in terms of energy consumption/production during a certain time span is specified with a standardized format as described in detail in [16]. For each appliance \( a \in \mathcal{A} \), the CS contains attributes describing a ‘valid from’ time \( v_{T_a} \) and a ‘valid thru’ time \( v_{T_a} \), stating the time interval from which the CS is valid and the time interval
until which the CS is valid. In addition, the CS includes the expiration time \( eT_a \), indicating before which time a decision has to be made on how to schedule the appliance. Let \( vF \) denote the earliest valid from time and \( vT \) the latest valid thru time as specified in each CS of all appliances \( a \in \mathcal{A} \). Then, for each appliance \( a \in \mathcal{A}_f \), the energy consumption over time of form \( f \) will be defined as \( x_{af} \) for the time interval \( vF \leq t \leq vT \), where

\[
x_{af} \triangleq \left[ x_{af}^{vF}, x_{af}^{vF+1}, \ldots, x_{af}^{vT-1}, x_{af}^{vT} \right].
\]

(1)

In this, \( x_{af}^t \) is the energy consumption (negative for energy production) of energy form \( f \) of appliance \( a \) at the time interval \( t \). This energy consumption \( x_{af} \) is constrained by the appliance’s flexibility space \( \mathcal{X}_a \) as described in the CS of the appliance. Here, \( \mathcal{X}_a \) is the set of all options for assigning a valid consumption pattern to the flexible appliance. Therefore, an energy allocation is valid if \( x_{af} \in \mathcal{X}_a \). Now, the total consumption vector for energy form \( f \) of all appliances \( a \in \mathcal{A}_f \) for the time interval \( vF \leq t \leq vT \) will be defined as

\[
I_f \triangleq \left[ I_f^{vF}, I_f^{vF+1}, \ldots, I_f^{vT-1}, I_f^{vT} \right]
\]

(2)

where

\[
I_f^t = \sum_{a \in \mathcal{A}_f} x_{af}^t.
\]

(3)

By stacking up the consumptions of all appliances \( a_f \in \mathcal{A}_f \), the energy consumption vector \( \mathbf{x}_f \) can be formed, combining the energy profiles over time of all appliances of energy form \( f \). Similarly, the two dimensional consumption ‘vector’ \( \mathbf{x} \) can be formed by stacking up the consumptions of all appliances \( a \in \mathcal{A} \), for both energy forms \( f \in [e, h] \) in a different dimension. This total stacked energy consumption vector \( \mathbf{x} \) is constrained by the two dimensional flexibility space \( \mathcal{X}_a \) of all appliances \( a \in \mathcal{A} \), where the dimensions of the flexibility space correspond with the two forms of energy. This way, \( \mathcal{X}_a \) forms the set of all feasible energy consumption schedules for \( \mathbf{x} \) and therefore allocations for energy consumption schedules are only feasible if \( \mathbf{x} \in \mathcal{X}_a \). In general, \( \mathcal{X}_N \) denotes the total flexibility space of the stacked consumptions of the appliances in the set \( \mathcal{N} \subseteq \mathcal{A} \).

C. Hybrid energy appliances

In this work, the HP is modeled as a conversion device, consuming electrical energy to produce thermal energy. The relation between electricity consumption and heat production of the HP is related by the coefficient of performance (COP), which indicates the ratio between produced heat and consumed electricity. The COP of a HP depends mainly on the efficiency, ambient temperature, ambient humidity and temperature of the heated water [20]. Although different studies show different relations between the compressor speed and COP as in [21] - [23], the differences in COP against power output of the HP are usually small. Therefore, in this paper the COP is assumed to remain constant for different output powers of the HP. The relation between electricity consumption \( x_{hp} \) and heat consumption (production is defined negative) \( x_{hp} \) of the HP at time interval \( t \) therefore is defined as

\[
x_{hp}^t = d_{hp} x_{hp}^t
\]

where \( d_{hp} = -\frac{1}{\text{COP}} \).

Similar to the HP, the CHP is modeled as a conversion device as well, consuming gas to produce both electricity and heat. The relation between electricity production and heat production of the CHP is given by the heat to power ratio (HPR), which indicates the ratio between produced heat and produced electricity. The HPR is assumed here to remain constant for varying power outputs. With this, the relation between electricity and heat consumption (both negative production) is defined as

\[
x_{c}^t = d_{c} x_{c}^t
\]

where \( d_{c} = \frac{1}{\text{HPR}} \). Note that it is not possible to feed back thermal energy through the CHP, as is the case with electrical energy through the grid connection. Therefore, in case of a surplus in thermal energy production from DER that cannot be consumed or stored, this thermal energy will be lost.

III. DECENTRALIZED ALLOCATION AND SCHEDULING

This section features the decentralized optimization, including cost model, optimization objective, distributed algorithm, and the local objective for the flexible appliances.

A. Energy cost model

The MC-SES may pursue various kinds of objectives, for example cost minimization, optimal local supply and demand matching, peak to average minimization, or maximizing the usage of renewable energy sources. This manuscript intends to optimize over the external resources, i.e. the electricity exchanged at the grid connection and gas (the district heating system is here modelled as a local network without external heat supply, only local supply from CHP, HP or for example solar boilers). The gas consumption is directly related to the amount of heat supplied by the CHP. Therefore, the optimization is performed over the electricity exchanged with the electrical grid and the heat supplied by the CHP.

When operating the system, the external electrical grid will cover all net remaining electrical energy demand or supply resulting from the (flexible) appliances and distributed energy resources (DER), including CHP and HP. Therefore, the electricity exchanged at the electrical grid is determined at each time interval \( t \) by the following:

\[
I_e^t = I_e^t + x_{hp}^t + x_{c}^t
\]

at each time interval \( t \). Since the amount of electricity \( I_e^t \)
exchanged with the electrical grid is an external resource, it is defined as billable unit, i.e., the unit to which (artificial) costs are assigned for operating the grid.

Just as is the case with the electrical grid, the district heating system should maintain a balance between the demand and supply of energy. In contrast to the LV electricity grid, the district heating system is not connected to an external thermal energy grid. Therefore, if there are \( A_h \subseteq [A_h \cup \{HP, \text{CHP}\}] \) appliances having thermal energy involved, the MC-SES can decide upon \( A_h - 1 \) appliances on how to schedule them, after which the \( A_h \)th appliance has to maintain the energy balance. Since the CHP is one of the most flexible appliances in the system, but above all is the appliance using external resources (gas) to generate energy and therefore causing costs, the CHP is selected as the balancing appliance in the district heating system. The amount of heat supplied by the CHP is defined as billable unit for thermal energy and for each \( t \) will be equal to

\[
L^t_h = I^t_h + x^{t}_{HP,h}.
\]

(7)

With this, for \( L^t_h \geq 0 \), the amount of electrical energy the CHP will consume (negative supply) is linearly related to the produced heat and therefore equal to

\[
x_{CHP,e}^t = d_{CHP}x_{CHP,h}^t = -d_{CHP}L^t_h.
\]

(8)

B. Optimization objective

Depending on the management objective, a cost function \( c_f^t(L^t_f) \) for time interval \( t \) can be assigned to the total electrical energy \( L^t_f \) exchanged with the electrical grid and the thermal energy produced by the CHP \( L^t_h \). These costs may represent either the actual costs of the energy produced, or artificial costs that help to achieve the management objective. In the latter, the cost function is designed such that when minimizing the cost function over \( X \) constrained to \( X_A \), the management objective is achieved. This way, the management objective can easily be changed by modifying the cost function. This paper will focus on optimal local supply and demand matching, therefore using as much locally generated renewable energy as possible, while spreading out the net remaining consumption and local production over time for both electrical and thermal energy. To achieve this, a cost function is used that is symmetrical around zero and strictly convex. This will cause the costs to rise faster when the exchange of electricity with the electrical grid or the thermal energy production increases. For computational simplicity, a quadratic cost function is used. With this, the objective of the MC-SES is represented as:

\[
\min_{x \in X_A} \sum_{t=vF}^{vT} \sum_{f\in(e,h)} c^t_f \cdot \left(L^t_f \right)^2
\]

(9)

with \( c^t_f > 0 \) for all \( vF \leq t \leq vT \). Examples of the constraints \( X_A \) of the various types of flexible appliances the MC-SES has to take into account are extensively described in [16]. Proper care must be taken with respect to the weighting factors \( c^t_f \) and \( c^t_h \) for external heat from the CHP (e.g. gas) and electricity. By changing the weighting factors, one may give higher priority to optimization of a specific resource. The weighting factor \( c^t_h \) for heat can even be set to zero, in order to fully optimize the heating system, supported by the heating system and multi commodity and thermal appliances. Note that this might imply high peak demands for gas.

When performing centralized optimization of (9), the advantage is that the optimization problem is formulated relatively straightforward and above all, the centralized optimization will result in the global optimum. As long as the constraints for \( X_A \) are linear, the problem of (9) will be solvable in polynomial time using quadratic programming [24]. However, due to the introduction of binary decision variables in the constraints of \( X_A \) as detailed in [16], mixed integer quadratic programming (MIQP) is necessary. This affects computation time, although limited size optimization objectives can be solved in reasonable time using branch and cut algorithms [25]. In order to deal with scalability of the optimization presented in (9), this paper proposes a decentralized optimization approach using a MAS.

C. Distributed algorithm

Based on [10], the MAS presented in this paper schedules the flexible appliances and resources in a decentralized way, where the optimization problem of (9) is divided in smaller, relatively easy to solve sub problems. By solving the local optimization problems using an iterative process, the algorithm will converge to the (sub) optimal solution. This involves only a limited amount of decision variables for each local problem, making the system highly scalable. As a disadvantage, sub optimal solutions may result from the fact that the decentralized optimization is composed of small sub problems, in which the agents are unaware of the flexibility offered from others. Therefore, the presence of discrete switching appliances may cause suboptimal solutions.

Within the MAS, each of the flexible appliances is represented by an appliance agent. Each appliance agent tries to optimize the energy consumption schedule \( x_a \) of its own appliance \( a \in A \), while taking into account the consumption vectors of all other appliances \( b \in A \setminus \{a\} \). Besides the appliance agents, an aggregator agent is present in the MAS. The aggregator agent is included to streamline and ease the exchange of information. It will collect the information of the individual consumption vectors \( x_a \) of each appliance \( a \in A \) and provide other appliances with this information. For privacy reasons, the aggregator agent can either supply an appliance agent \( a \in A \) with information about the total sum of consumption patterns \( I_f \) of all appliances \( b \in A_f \), or with the newly defined consumption vector \( L_{-a_f} \) being the sum of the consumption patterns for energy form \( f \) of all other appliances \( b \in A_f \setminus \{a\} \). Here, \( L_{-a_f} \) is defined as:

\[
L_{-a_f} = \left[ l_{-a_f}^{vF}, l_{-a_f}^{vF+1}, ..., l_{-a_f}^{vT} \right].
\]

(10)
where the sum of electrical energy consumptions $l_{u_{a_f}}$ at time interval $t$ of all other appliances $b \in A_f \setminus \{a\}$ is equal to

$$l_{u_{a_f}} = \sum_{b \in A_f \setminus \{a\}} x_{b_t} \tag{11}$$

The time horizon of the iterative algorithm is a sliding window. All flexible appliances construct a CS valid in this time window and update the corresponding allocation continuously, until the time at which the most recent version of the allocation needs to start. An advantage is that the distributed algorithm can easily deal with the unsynchronized release of a new CS in time, without aligning with the CS from other appliance agents. Since each agent only solves the local optimization problem of the appliance it represents, the optimization of the local problem can immediately start once a new CS is created. The agent representing the appliance can independently decide on how long it wants to participate in the distributed algorithm and therefore it can make sure that the expiration time $eT_a$ of the CS can be met and the allocation can be started at the optimal time as calculated in the latest allocation. After execution of the optimal allocation, a new CS will be constructed by the appliance, valid in the new window that has moved over time.

The iterative algorithm is detailed in Algorithm 1. As soon as an appliance agent receives a CS from its appliance, it will start with its first iteration. For this, it will request the aggregator agent for the most actual consumption vectors $l_f$ or $l_{a_f}$, depending on which is necessary from the optimization objective. Based on this information, the appliance agent will optimize the consumption of its own appliance $x_a$, of which the objectives for each type of appliance are detailed in the next section. The objectives are constrained to the appliance ‘flexibility space’ $X_a$ and taking into account the consumption patterns $l_f$ or $l_{a_f}$ of other appliances as a fact, not as a decision variable. The result of the optimization will be submitted to the aggregator agent, after which other appliance agents can take this result into account. From now, at random time intervals $\tau$, where $0 < \tau < R$ with $R$ being the upper bound of the time interval, the appliance agent can start a new iteration, repeating the optimization, each time based on the most actual consumption vectors $l_f$ or $l_{a_f}$. After each iteration, the appliance agent will submit a new $x_a$ to the aggregator if $x_a$ has changed compared to the previous consumption schedule. This process continues for each appliance until the expiration time $eT_a$ of the CS for that appliance has been reached, or if the allocation as calculated in the latest iteration for that appliance has to start. Once stopped participating in the algorithm, the consumption vector $x_a$ will not change anymore, but will of course be taken into account by other appliances that are still participating in the distributed algorithm. This way, the optimization for all appliances is performed in a decentralized and iterative way, where the schedules are continuously updated according to the latest available consumption schedules of all appliances.

**Algorithm 1:** Executed by each appliance agent $a \in A$

1. Receive CS from the flexible appliance
2. Request aggregator for $l_f$ or $l_{a_f}$
3. Receive $l_f$ or $l_{a_f}$ from aggregator agent
4. Optimize $x_a$ using MIQP or otherwise
5. Send control message to aggregator to update $x_a$

Repeat

7. At random time instances $\tau$ with $0 < \tau < R$ Do
6. Request aggregator for $l_f$ or $l_{a_f}$
9. Receive $l_f$ or $l_{a_f}$ from aggregator agent
10. Optimize $x_a$ using MIQP or otherwise
11. If $x_a$ changes compared to current schedule Then
12. Update $x_a$ according to new solution
13. Send control message to aggregator to update $x_a$

End

Until $eT_a$ or start of most recent optimal allocation $x_a$

Apply most recent allocation to the flexible appliance

**D. Objectives of flexible appliances**

Here the local optimization objectives for the various flexible appliances will be treated. This optimization objective forms the local decision problem solved by the representing appliance agents. The consumption vectors of the CHP follow from the optimization of all other appliances according to (7) and (8). Therefore, the CHP is not represented by an appliances agent. Instead, its consumption vectors are updated by the aggregator agent, each time it receives an updated consumption vector from another appliance agent.

1) Heat pump

For the HP, the objective is quite straightforward, and follows directly from (9). The minimization objective of the HP should consider both its electricity consumption $x_{HP_e}$ as well as its heat ‘consumption’ $x_{HP_h}$, together with the total electricity consumption and heat consumption of all other appliances $l_{HP_e}^t$ and $l_{HP_h}^t$. Besides, it should take into account that in case part of the heat demand from the thermal appliances will be produced by the CHP, the CHP will also produce electrical energy. Therefore, the electricity ‘consumption’ $x_{CHP_e}$ of the CHP will be included as a decision variable. From (8), the amount of electricity produced by the CHP can be expressed in terms of the CHP heat production for every time frame $nF \leq t \leq nT$, which will be included as a constraint. It is important to note that, although the electricity ‘consumption’ $x_{CHP_e}$ of the CHP is calculated, it will not be applied by the agent representing the HP. Instead, the schedule of the CHP will be adjusted by the aggregator agent as soon as it receives the updated $x_{HP}$ from the appliance agent representing the HP. With this, the optimization objective of the HP, taking into account the consumptions $l_{CHP}$ of all other thermal and electrical appliances, becomes:

$$\min_{[x_{HP}, x_{CHP}] \in [H_{HP}, H_{CHP}]} \sum_{t=nF}^{nT} \left[ c_{h}^2 \cdot (x_{HP_h}^{t} + l_{HP_h}^t)^2 + c_{e}^2 \cdot (x_{HP_e}^{t} + l_{HP_e}^t + x_{CHP_e}^{t})^2 \right]$$

(12)
Rewriting optimization objective (12), given that \(x^e_{HP} = d_{HP}x^e_{HP_h}\) from (4), under the constraint that
\[x^e_{CHP_e} = \min(-d_{CHP}(x^e_{HP} + l^e_h), 0)\]
from (8), results in an objective function with only \(x^e_{HP_h}\) and \(x^e_{CHP_e}\) as a decision variable. Note that the ‘min’ function is nonlinear. It is possible to introduce a mixed integer linear constraint for the ‘min’ function by creating a binary if-then-else condition [26].

2) Electric and thermal appliances

Electric and thermal appliances should not only be aware of the consumption of their own form of energy, but also of the other form. For example, electric appliances may align with thermal appliances in order to make operation of the CHP more profitable. The other way around, thermal appliances can align with electric DER to operate the HP more efficiently. Besides, whether the thermal energy demand is (partly) supplied by the HP or the CHP also has consequences for the electricity exchanged with the MV grid. Therefore, it is important to know the behavior of the HP for both the electric and thermal appliances. To do so, the appliance agent representing an electric or thermal appliance, will also (re)calculate the optimal schedule of the HP, together with the optimization of its own appliance. Similar to the case of the HP, also the electricity ‘consumption’ \(x^e_{CHP_e}\) of the CHP is calculated. It is important to note that, although the optimal schedule of the HP is calculated, it will not be applied by the appliance agent. The schedule of the HP will be adjusted as soon as the appliance agent representing the HP performs a new optimization by itself, whereas the aggregator agent will take care of the schedule of the CHP. The resulting minimization objective for every electric appliance \(a \in A_e\) is:

\[
\min_{[\mathbf{x}_a, \mathbf{x}_{HP}, \mathbf{x}_{CHP}] \in \mathcal{E}_{[a, HP, CHP]}} \sum_{t \in \mathcal{D}} c^t_e \cdot \left( l^t_e + x^e_{HP_h} \right)^2
\]

\[
\quad + c^t_a \cdot \left( x^t_{a_e} + l^t_{a_e} + x^t_{HP_h} + x^t_{CHP_e} \right)^2.
\]

Rewriting optimization objective (13), given that \(x^e_{HP} = d_{HP}x^e_{HP_h}\) from (4), under the mixed integer constraint that
\[x^e_{CHP_e} = \min(-d_{CHP}(l^e_h + x^e_{HP}), 0)\]
from (8), results in an objective function with only \(x^e_{a_e}, x^e_{HP_h}\) and \(x^e_{CHP_e}\) as a decision variable. Similar, the resulting objective function every thermal appliance \(a \in A_t\) yields

\[
\min_{[\mathbf{x}_a, \mathbf{x}_{HP}, \mathbf{x}_{CHP}] \in \mathcal{E}_{[a, HP, CHP]}} \sum_{t \in \mathcal{D}} c^t_h \cdot \left( x^t_{a_e} + l^t_{a_e} + x^t_{HP_h} \right)^2
\]

\[
\quad + c^t_e \cdot \left( l^t_e + x^t_{HP_e} + x^t_{CHP_e} \right)^2.
\]

Rewriting optimization objective (14), given that \(x^e_{HP} = d_{HP}x^e_{HP_h}\) from (4), under the mixed integer constraint that
\[x^e_{CHP_e} = \min(-d_{CHP}(l^e_h + x^e_{HP}), 0)\]
from (8), results in an objective function with only \(x^e_{a_e}, x^e_{HP_h}\) and \(x^e_{CHP_e}\) as a decision variable.

### IV. Experimental results and discussion

In order to compare the performance of the decentralized approach with the centralized approach, both algorithms have been verified using a practical test case. The test setup consists of six flexible appliances, including four electrical and two thermal appliances together with a HP and CHP. They are modelled in an object oriented way in MATLAB. Each of the appliances is represented by its own appliance agents, which are together with the aggregator agent implemented using the Java Agent Development Framework (JADE) [27]. The optimization in each of the appliance agents is carried out using MOSEK [28]. The appliances offer flexibility within a 24 hours sliding window, with a granularity (time interval length) of one hour. The COP and HPR of the HP and CHP are both set to be equal to 1. For the optimization objective, \(c^t_e\) is set to 1 for \(f \in \{e,h\}\) and \(t\). The graphs in Fig. 2 show allocations of the individual appliances. In this, the thick lines represent electrical appliances, while the thin lines represent thermal appliances. Blue continuous lines are for buffering appliances, which may consume energy from the first dot at \(vF_0\) to the second dot at \(tT_a\), at which they need to reach a certain SoC. The red dashed lines are for time shifting appliances who need to follow the specified pattern somewhere in between the two dots at \(sA_a\) and \(sB_a + P\). Magenta dashed lines are for appliances that offer no flexibility and just follow the pattern. Last but not least, the lowest graph in Fig. 2 is for the HP, showing both the electricity and heat ‘consumption’.

#### A. Optimization performance

The graphs in Fig. 3 display the results of the distributed algorithm applied to this test case, showing the amount of power over time that is exchanged with the external grid (blue continuous), as well as the heat that is supplied by the CHP (red dashed). Negative heat supply means local produced heat by DER that is lost. The results presented are for the moment the algorithm is started for the first time. For this reason, all appliances construct their first CS at that moment. The upper graph of Fig. 3 shows the schedule of the distributed algorithm after each appliance has performed its first iteration. Note that this schedule is already more optimal than just starting the appliances on the first possible occasion, but still shows a lot of peaks for both electricity and heat. The lower graph of Fig. 3 shows the schedule after the distributed algorithm converged. Here, convergence is denoted as the point at which \(\mathbf{x}_a\) for any appliance \(a \in A\) will not change any more when performing a new iteration. For the results presented, no new CSs have been submitted and no existing CSs has been changed from the start of the algorithm until convergence.

It can be seen that in contrast to the upper graph of Fig. 3, in the lower graph of Fig. 3 the supply and demand are nicely matched and spread out over time. After running the centralized algorithm from [16] for the same test case, it turns out that the results shown in the lower graph of Fig. 3 are the optimal schedule and exactly equal the centralized schedule. The individual schedules of the appliances presented in Fig. 2 correspond with the optimal schedule as displayed in the lower graph in Fig. 3. The graphs in Fig. 2 show that each appliance...
has been scheduled such that the supply and demand are matched as best as possible for both electrical and thermal appliances. For the HP, it can be seen that it starts producing heat when there is a high demand for thermal energy together with low electricity consumption. Also note that part of the electricity is also supplied by the CHP. This is not shown in Fig. 2, but can be derived from the thermal energy production of the CHP as displayed in Fig. 3.

In the test case presented in Fig. 2 and Fig. 3, the decentralized approach resulted in the global optimal schedule, equal to the schedule of the centralized approach. In order to show how the distributed algorithm can end up in a local minimum, both approaches have been applied to another test case, including several electric buffer and time shifting appliances. The graphs in Fig. 4 show the schedules of centralized approach and the decentralized approach after convergence. As a reference, also the schedule of the decentralized approach after each appliance has performed its first iteration, is displayed. Compared to the schedule of the first iteration, the electricity supply has nicely flattened out after convergence of the decentralized approach. However, it can be seen that there is a small difference with the results of the decentralized approach, where the total artificial costs for the decentralized approach are slightly higher than for the centralized approach. This is a result from the fact that the centralized approach is a little more flattened out, and therefore more optimal compared to the decentralized approach, which is also reflected in the costs. When looking at the individual differences of the schedules between the centralized and the decentralized approach in this second test case, it turns out that in the decentralized approach one of the time shifter appliances has shifted its consumption to another position and gets 'trapped' inside the schedule of some buffer appliances. The time shifter appliances in the decentralized approach are unaware of the fact that the buffer appliances can possibly adapt to better starting times of the time shifter. In contrast, in the centralized approach the optimization is carried out with the whole picture in mind, preventing the time shifter to end up in the local minimum. Therefore, when including discrete switching appliances like the time shifter appliance, the decentralized approach might end up in a local minimum.

A 1000 Monte Carlo simulations were performed, each time with 25 appliances of different types being randomly initialized (i.e., random valid from $vF$ and valid thru $vT$ time, start after $sA$ and start before $sB$ time, consumption vector $p$, target time $tT$ and target SoC). This resulted in a mean absolute percentage error (MAPE) over the square root of the cost function (9) of 2.07% between the centralized and the converged decentralized approach. When the number of participating appliances was increased from 25 to 100, the MAPE reduced to 0.18%. When excluding time shifter appliances from the simulation, the MAPE reduced to values related to the solver tolerance. Therefore, for the simulations performed, in general the difference between the decentralized and centralized approach is relatively small, especially compared to the difference when scheduling without optimization (i.e., starting all appliances at the first occasion).
B. Algorithm complexity

Fig. 5 displays how the artificial energy costs evolve with the number of iterations when running the distributed algorithm. In this, the costs are normalized to the costs of the first iteration. Shown are the costs for different numbers of appliances, averaged over a large amount of simulations, with randomly initialized appliances. It can be seen that the algorithm converges after each appliance has performed three to four iterations, independent of the number of participating appliances. Therefore, for the number of appliances shown in Fig. 5, the algorithm scales linearly when performing the iterations sequential. However, in a practical situation the iterations will be performed even partly in parallel, due to the randomly instantiated time instances \( \tau \) at which the iterative optimizations are started by different appliance agents. This results in another performance increase, especially for a large amount of participating appliances. Besides, as stated in section IV.A, the results presented are from the moment the distributed algorithm is started for the first time, when all appliances construct their first CS. This means that the changes in the allocations are relatively large. However, when time progresses, appliances create a new CS or update the current one more spread over time, causing the changes in the iterative optimization of the allocations to be less severe. Therefore, throughout execution of the platform, the allocations will generally converge faster than the results presented. Since the local decision problem concerns a highly limited amount of decision variables, a single optimization iteration of an appliance can be carried out in a very small amount of time. Therefore, the absolute time to converge depends mainly on the average random time instance \( \tau \) between the repetitive iterations and the number of participating appliances. Future works needs to be carried out to determine the optimal mean and standard deviation for \( \tau \) as function of the number of appliances and communication delays. Interestingly, the larger the number of appliances, the closer the average costs at the first iteration are to the average costs after convergence. This can be explained by the fact that with more participating appliances, there is a large amount of flexibility. For the same reason, a sub-optimally scheduled appliance will more easily be compensated by others.

V. CONCLUSIONS AND RECOMMENDATIONS

In this paper, existing research for a MC-SES management approach has been extended by developing a decentralized management approach. The decentralized algorithm has been shown to achieve similar optimization performances compared to the centralized approach. Therefore, it proofs suitable for performing local supply and demand matching in a MC-SES for both electricity and heat. Significant improvements in the usage of locally generated energy can be achieved, especially when using the hybrid energy appliances as the HP and CHP. This can drastically reduce energy costs, carbon emissions and operating costs of the energy system. The decentralized approach offers an efficient way for dealing with scalability as well as flexibility due to the small local optimization problems. Due to this, solving the local problem is in principle not restricted to using MIQP. Therefore, the results of this paper can be improved by developing more advanced models of the flexible appliances that offer more accuracy.

VI. REFERENCES


Niels Blauwbroek (S’10) was born in Assen, the Netherlands, on November 21, 1989. He received his BSc and MSc degree in Electrical Engineering from Eindhoven University of Technology, the Netherlands in 2012 and 2014 respectively. From August 2014, he is working as a PhD student at the Electrical Energy Systems (EES) group at Eindhoven University of Technology, where his research is focused on real time monitoring and control of distribution networks.

Phuong H. Nguyen (M’06) received the Ph.D. degree in electrical engineering from Eindhoven University of Technology, in 2010. He is an assistant professor in the Electrical Energy Systems group, Eindhoven University of Technology. He was a visiting researcher with the Real-Time Power and Intelligent Systems (RTPIS) Laboratory, Clemson University. His research interests include distributed state estimation, power system control and operation and multi agent systems.

Mente J. Konsman finished his Artificial Intelligence studies in 1999 at the University of Groningen. He started working for KPN Research where his main focus was on Telecommunications Management and Enterprise Application Integration. From 2003, at TNO he contributed to the design and implementation of a software platform (AnySense) to collect and distribute sensor data. In the last couple of years he mainly worked on developing the Flexible Power Application Infrastructure.

Huaizhou Shi (1984-) received his PhD from Delft University of Technology in 2014. He is currently working as a Postdoc researcher in Electrical Energy Systems Group in Eindhoven University of Technology. His research interests include smart grid, smart cities, wireless communications, resource allocation related issues and fairness study in general.

René (I. G.) Kamphuis (1952) is a Senior Research Technologist at TNO and a part-time professor in “Smart operation of electricity systems through ICT” at Eindhoven University of technology. He is the founder and developer of agent-based coordination techniques for supply-demand matching of energy and for implementation in energy and electricity markets. His contributions are also to ICT architecture, design and development for SmartGrids living labs.

Wil L. Kling (M’95) is a full professor and chair of Electrical Energy Systems group, Eindhoven University of Technology. From 1978 to 1983 he worked with Kema, from 1983 to 1998 with Sep and from 1998 to 2008 with TenneT, as senior engineer for network planning and network strategy. Since 1993 to 2010 he was part-time Professor at the Delft University of Technology. He is leading research programs on distributed generation, integration of wind power, network concepts and reliability issues.