Perspectives

Developing an Algorithm to Consider Mutliple Demand Response Objectives

Applying an Algorithm Engineering-Oriented Approach for the Residential Context

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***Abstract*—Due to technological improvement and changing environment, energy grids face various challenges, which, for example, deal with integrating new appliances such as electric vehicles and photovoltaic. Managing such grids has become increasingly important for research and practice, since, for example, grid reliability and cost benefits are endangered. Demand response (DR) is one possibility to contribute to this crucial task by shifting and managing energy loads in particular. Realizing DR thereby can address multiple objectives (such as cost savings, peak load reduction and flattening the load profile) to obtain various goals. However, current research lacks algorithms that address multiple DR objectives sufficiently. This paper aims to design a multi-objective DR optimization algorithm and to purpose a solution strategy. We therefore first investigate the research field and existing solutions, and then design an algorithm suitable for taking multiple objectives into account. The algorithm has a predictable runtime and guarantees termination.**

Keywords-optimization; demand response; demand side management; algorithm engineering; greedy heuristic

I. MOTIVATION

Nowadays, because of technological improvements and changing environment, energy grids are facing various challenges, such as growing energy demand, new consumption patterns through new living behaviors and emerging economies and therefore rising pollution (e.g., carbon emissions) [1]. As a result, sustainable concepts such as renewable energy (e.g., photovoltaic (PV), wind and water) that is moreover often used in a decentralized way and new appliances, especially electric vehicles (EVs) are implemented [2]. These concepts thereby result in a more volatile energy generation and consummation that affects both supplier and consumer. Effects of these might be critical peaks, contingencies, a volatile load profile, and disadvantages in the market performance as well as an insufficient infrastructure usage. These can result in blackouts, brownouts, shortages, a high spinning reserve and can endanger energy grid reliability. Especially residential context management faces major transformation—for example, increasing implementation of EVs and decentralized energy generation as well as new storages—and can contribute to this problem, as the energy consumed in this sector is about 38% of the total consumption and therefore worthy enough to be in our scope [3]. However, to support these situations, a management of new appliances in energy grids is necessary.

One possibility to manage appliances in such grids is given by demand response (DR). DR focuses on optimizing consumption patterns, for example, according to external signals (e.g., pricing signals). Therefore, DR uses algorithms which can be heterogeneous regarding addressed objective, optimization methods or communication structure [4]. Optimization in DR is carried out by shifting or managing loads which is provoked by incentive-based programs [5] such as different types of dynamic pricing (e.g., time-of-use pricing (ToUP), critical-peak pricing (CPP), and real-time pricing (RTP) [6, 7]). In order to allow using dynamic pricing, different infrastructure (smart metering, controlling and communication mechanisms) is required. Due to the fact that the existing infrastructure is not widespread, a popular dynamic pricing scheme is ToUP with two different pricing intervals: a low pricing interval in the off-peak hours (usually in the night and the early morning) and a high pricing interval during the peak hours. This approach has the advantage that the pricing signal is known and predictable, and the communicational effort is low. However, this mostly generic and simple approach may result in misleading incentives—for example: a user, switching on all deferrable devices at the time the lower pricing interval starts. Thus, a new peak is created and the load profile is fluctuating. Consequently, we need a pricing that does (i) not need further infrastructure and (ii) addresses the misleading incentive from ToUP. A possible solution is, based on the ToUP, to provide a pricing function that extra charges the additional peaks and a fluctuating load profile or benefit if additional peaks are avoided and a flattened load profile is achieved. Similar types of pricing signals/tariffs already exist [8], for example, pricings that (a) try to deliver a load depended pricing function, (b) deliver a critical peak pricing signal or (c) combine three different pricing intervals and a fourth, optional, pricing phase during peak hours. In order to achieve cost-savings with the new pricings, consumers need to respect not only the time-of-use of appliances, but also peak load reduction and load profile flattening.

However, current DR algorithms usually take a single factor or objective into account (e.g., costs or peak-load reduction [9, 10]). Thus, we currently lack the considering of multiple relevant factors. Particular algorithms try to combine different goals, for example, to minimize costs and maximize the comfort level of users [10–12]. Authors in [13] identified four objectives, addressing major DR goals: lower energy consumption, peak load reduction, load profile flattening and cost reduction. Authors in [14] address multiple goals, however, the resulting optimization problem gets complex and challenging to solve. They therefore propose a greedy algorithm to find a solution. Nevertheless, to use this algorithm, an extensive amount of data is needed, and thus, the optimization is slow, and the communication and computational costs are high. Hence, a possible solution to optimize the usage with DR in the stated pricing scheme, is to address multiple objectives simultaneously. However, we currently lack the research that contributes to the achievement of multiple goals at the same time while requiring less information, due to reduced communication and calculation costs [10], and is also easy to implement. This study reports on the design, implementation and analysis of a particular algorithm which is capable of considering multiple DR-objectives. With this new algorithm several stakeholders can benefit such as (a) users as they can reach several goals (e.g. realize cost savings and maximize welfare), (b) energy providers as they can give more incentives to the users and thereby achieve more efficient generation or predictability, (c) energy grids can get more stable and can react more flexible on contingencies, (d) appliances (e.g. EVs) and infrastructure (e.g. storages and PVs) will be embedded in a more fertile way, (e) emissions will be reduced, and (f) acceptance of DR may increase.

II. RELATED WORK

A. Methods and Algorithms in the DR Field

In order to identify solution concepts for an algorithm suitable for realizing multiple goals and to ensure that no research exists which already answers our research question sufficiently, we conducted an extensive literature search. Moreover, [15–17] conducted literature reviews in the field and were consequently considered as well. One finding is, that especially the supplier side has been in the focus in this research field (e.g., the Trading-Agent-Competition deals with the question, how energy suppliers can give an optimal pricing signal to the consumers, according to a given set of energy demand and predicted consumption [18]). Focusing on the consumer side, to the best of our knowledge, we could not identify any appropriate solution. Addressed goals thereby are heterogeneous such as cost reduction [19–21] or peak load reduction [22–24]. Some algorithms try to achieve two goals simultaneously, for example, reducing costs while maximizing users' comfort (or at least retain a certain comfort level) [25–28]. These goals are often realized on the basis of a cost function which is externally given by an energy supplier and the comfort level is considered as an additional condition to the objective function. Authors in [14] considered multiple goals, however, these are not suitable for answering our research question sufficiently, as multiple and difficult to solve optimization functions are used. Moreover, authors in [13] identified multiple-objectives that can be achieved when implementing DR in the residential context. The optimization problem is constructed with multiple objective functions, each optimizing towards one goal (load profile flattening, cost reduction, comfort maximization, peak load reduction). However, multiple objective functions mostly return in a complex problem and the solution therefore is more difficult. Hence, we could not identify any research, answering our research question sufficiently. However, we get an idea, how a possible algorithm could be arranged.

B. Model from the DR Field

The main goal of our study is to consider several objectives. A constrained multi-objective optimization problem (CMOP) is defined as follows [10, 29] (x =vector of inputs):

$$F(x) = [f_1(x), f_2(x), ..., f_k(x)] \quad (1)$$

Under the additional conditions ($g()$ and $h()$ =conditional functions):

$$g_i(x) = 0 \quad i = 1,..., m \quad (2)$$

$$h_j(x) < 0 \quad j = 1,..., n \quad (3)$$

Under certain assumptions, a pareto-optimal solving strategy can be found, however, often this is not given because the optimization model is too complex. Some DR models can be traced back to this generalized model [13]. Because we want to derive a single optimization function model and we have to consider several constraints regarding the appliances [30] to meet the application area, we choose the optimization model of [31], based on [30], which aims at reducing the costs of the overall system with the help of a ToUP, which can be exchanged to several other DP alternatives. Our model uses the following variables:

Let N be all considered living units and A_n be all the appliances of living unit $n \in N$ and ω be the sample rate of the discrete model (number of time periods) over one day. Moreover, let $x^h = \sum_{n \in N} \sum_{a \in A_n} h^h_{n,a}$ with $h \in Z = \{0,1,..., \omega\}$ be the sum of all appliances $a \in A_n$ of all living unit $n \in N$ in the timeslot h.

Let $l_{n,a}^{k}$ be the load profile in a local time interval $k \in T_l = \{0,1,...,\delta_{n,a}\}$, $l_{n,a} = \sum_{k \in T_l} l_{n,a}^{k}$ the load sum and $\delta_{n,a}$ the length of load $a \in A_n$. In doing so, we can transform a given horizontal and inseparable load profile from its local time interval T_l to the global one T through shifting the whole T_l by an appropriate constant $m_{n,a}$, i.e., $h_k = k + m_{n,a}$ with $0 \le m_{n,a} \le \omega - \delta_{n,a}$.

Furthermore, let $\gamma_{n,a}^{h,\min}$ be the min and $\gamma_{n,a}^{h,\max}$ be the max borders for a load $x_{n,a}^{h}$ with $h \in T$, $a \in A_n$ so we can specify, in which borders the intensity of load a can be shifted, i.e., $\gamma_{n,a}^{h,\min} \le x_{n,a}^{h} \le \gamma_{n,a}^{h,\max}$. We note that the given load profiles have to satisfy $\gamma_{n,a}^{h,\min} \le l_{n,a}^{h_k} \le \gamma_{n,a}^{h,\max}$ for all $k \in T_l$ to get a feasible solution.

Let $\alpha_{n,a}$ be the starting and $\beta_{n,a}$ be the ending time slot of a load for an appliance α, then we can restrict time interval T to $[\alpha_{n,a}, \beta_{n,a}]$. We note that the interval length between $\alpha_{n,a}$ and $\beta_{n,a}$ has to be at least the length of the load profile $\delta_{n,a}$. to get a feasible solution, i.e., $\beta_{n,a}-\alpha_{n,a} \geq \delta_{n,a}$.

Turning a constraint i on and off for each appliance a individually let $c_a^i \in \{0,1\}$ be a binary variable that shows if a constraint is turned on or not for the appliance α.

The objective function describes the costs of the given load profiles, while the cost in a timeslot h is a function depending on h and the total load x^h i.e., $c^h = c(h, x^h) * x^h$.

$$\min_{x_{n,a}^{h}} c = \sum_{h=0}^{\omega} c^{h} = \sum_{h=0}^{\omega} c(h, x^{h}) * x^{h} \tag{4}$$

$$\sum_{h=0}^{\omega} x_{n,a}^{h} = l_{n,a} \quad \forall n \in N, a \in A_n \tag{5}$$

$$(x_{n,a}^{h_k} - l_{n,a}^{k}) * c_a^1 \qquad \begin{array}{l} \forall k = 0,...,\delta_{n,a}, \\ \forall n \in N, \forall a \in A_n \end{array} \tag{6}$$

$$\begin{array}{l} (x_{n,a}^{h} - \gamma_{n,a}^{h,\max}) * c_a^2 \le 0 \\ (\gamma_{n,a}^{h,\min} - x_{n,a}^{h}) * c_a^2 \le 0 \end{array} \qquad \forall n \in N, a \in A_n \tag{7}$$

$$(\sum_{h=\alpha_{n,a}}^{\beta_{n,a}} x_{n,a}^{h} - l_{n,a}) * c_a^3 = 0 \qquad \forall n \in N, a \in A_n \tag{8}$$

$$x_{n,a}^{h} \ge 0, c_a^i \in \{0,1\} \qquad \begin{array}{l} \forall h \in T, n \in N, \\ a \in A_n, i = 1,2,3 \end{array} \tag{9}$$

III. RESEARCH METHODOLOGY

Due to the fact that we want to create a new artifact, our research methodology follows the Design-Science-Research (DSR) paradigm [32]. Moreover, for designing an algorithm, we found two different approaches: (a) "algorithm theory" (AT) and (b) "algorithm engineering" (AE) [33]. AT focuses on the formulation of the mathematical model and afterwards proofs that it finds an (optimal) solution in a guaranteed time. AE addresses the application area, which gets more important nowadays, as data volume, real time computing, etc. is getting more complex. This approach does not aim at proofing a guaranteed time and optimization for all possible inputs but rather to guarantee a good performance and result for common inputs of the application area. The evaluation is carried out with an experiment, which is an inductive reasoning approach. The AE approach consists of five different (main) steps: modeling the application area as basis for the design phase, followed by the analysis of the designed algorithm, implementation of the algorithm and finally the evaluation. These steps have a strong relationship to the application, receiving application depending information (e.g. input data or the mathematical model) or contributing to the application (e.g. delivering a library to use or giving a performance guarantee). Because the DR context, as our application area, is a complex field [34], we assume the AE approach as more suitable. Moreover, the evaluation in the DSR field should focus the real world problem, respectively the application area [35].

IV. DESIGN

A. Adapted Optimization Model

The stated model (section II.B) aims at cost reduction. For expanding this, we need to identify suitable objectives in the field in order to design an optimization model. Authors in [13] identified several objectives that need to be integrated in the optimization model. These indicators match with most of the DR objectives, such as peak load minimization, load profile flattening, reliability ensuring, market performance maximization or utility and welfare maximization. As these are additional objectives, they need to be included in the optimization function (done in [13] in a generalized form for a single home). Nevertheless, authors use multiple optimization functions, which result in an even more complex problem and the algorithm gets inefficient, for example, regarding the calculation time [31]. We therefore need less objective functions [33]. Our main goal is to design an optimization model with only one objective function, thus, we need to consider all goals there. One approach, as the cost function is already integrated in the stated model, could be realized with the help of 'penalty costs'. The basic idea is that all three objectives influence a cost factor, which then, based on a kWh price, gives the costs a certain timestamp for placing the load. The objective function is formulated in the following way, over the optimization horizon: $\min_{x_{n,a}^{h}} c = \sum_{h=0}^{\omega} c(\theta) * x^{h}$, where θ is the vector of additionally needed information to calculate the penalty costs.

First of all, the timeslot is needed to consider time dependent costs (e.g. ToUP or CPP). In order to achieve a flattening of the load profile, measured for example by the Mean-Squared-Error (MSE), the fluctuation needs to be minimized. Therefore, we implement rising penalty costs for deviations from the arithmetic mean of the last X timestamps. This means, if the placement of a certain load in timeslot Y rises or lowers the consumption in that timeslot more than a certain percentage compared to the arithmetic mean of the last

X timeslots, the cost factor is raised and penalty costs are added. The same procedure is chosen to integrate a more effective peak load reduction. If the placement in timeslot Y will create a new peak, the cost factor should be raised by a certain percentage.

At this point, two upcoming questions must be answered: first, how can the additional information be gathered and, second, how do the penalty costs look like. The penalty costs need certain parameters, which need to be instantiated (filled with concrete values). For example, how much are the penalty costs increasing when creating a new peak? However, because the selection of the concrete values does not influence the performance of the algorithm according to its runtime, we do this in the following analyzation phase. The objective function now looks the following:

$$\min_{x_{n,a}^h} c = \sum_{h=0}^{\omega} c^h = \sum_{h=0}^{\omega} c(\theta) * x^h \tag{10}$$

Both function *c()* and vector θ still need to be defined. θ needs to involve information about the timestamp *h*, the load in this timestamp x^h, the arithmetic mean of the last j timestamps *MEAN(h-j)* and the actual peak load *PEAK*. Moreover, parameters for (a) the cost function (a ToUP with two different intervals for low price (LP) and high price (HP) is chosen) with additional information, such as costs in different intervals and interval lengths, (b) increasing cost rate ρ for σ% of deviation from the mean, and (c) increasing cost rate τ for a new peak are needed.

$$c(\theta) = c(h, x^h, MEAN\ (h-j), PEAK\ ) = \tag{11}$$

$$c_1 \rightarrow \begin{cases} c_1 = LP & : 0 \le h \le a; b \le h \le \omega \\ c_1 = HP & : a < h < b \end{cases}$$

$$+ c_2 \rightarrow \begin{cases} c_2 = 0 & : 0 \cdot \sigma \\ c_2 = c_1 \cdot \rho \cdot 1 & : 1 \cdot \sigma \\ c_2 = c_1 \cdot \rho \cdot 2 & : 2 \cdot \sigma \\ \ldots \end{cases} \le \frac{|x^h - MEAN(h - j)|}{x^h} \begin{matrix} < 1 \cdot \sigma \\ < 2 \cdot \sigma \\ < 3 \cdot \sigma \\ \ldots \end{matrix}$$

$$+ c_3 \rightarrow \begin{cases} c_3 = c_1 * \tau : x^h \ge PEAK \\ c_3 = 0 \quad : sonst \end{cases}$$

B. Needs for Additional Information

The initial optimization model requires a cost function, depending on the timeslot and the amount of energy consumption in this timeslot. This information is suitable for most pricing schemes such as ToUP and RTP. By using the new objective function, we now need further information about the arithmetic mean of the last j timeslots and the highest peak so far in the overall load profile. Depending on the control scheme (e.g. [4]), this information can be given on different ways:

- Autonomous control: This control scheme has no communication and a local decision making. Therefore, the local controller can only access local information and the optimization is done based on this information. However, this local information should be easily accessible because the local controller has not to deal with security and privacy concerns [36].
- Direct control: In this case (one or two way communication) the centralized controller has all the needed information and the decision making about the load shifting is made directly. However, we have to deal with privacy concerns etc.
- Indirect control and transactional control: In both cases the decision making is done locally. However, because of the one or two way communication infrastructure, the information needed can be send either from the central controller or the other users. Besides privacy concerns, it has to be argued, which information is used: only each user's local information of or the overall information from the grid.

C. Possible Solving Strategies

In order to solve the stated optimization problem, we need a suitable method. EAs have proven to be effective in finding good approximations of CMOPs' optimal solutions, as stated in [10]. Other possibilities are greedy, hill-climbing or branch-and-bound algorithms [37, 38]. The greedy heuristic is a method relatively easy to implement with a guaranteed runtime and already known in the DR field. Especially the runtime needs special attention here. Hence, we choose the greedy heuristic. However other heuristics are possible too. Solving the optimization problem with the greedy heuristic can be done in two different ways. The classic greedy algorithm—in the DR field—sorts all shiftable loads either downward or upward according to their (summarized) consumption. This means, the biggest or lowest load is picked first. Afterwards, the load is placed in the "best" timeslot. No matter which sorting strategy is chosen, we need to identify the best timeslot to place the picked load afterwards. In former greedy applications, this is, for example, the place with the lowest energy consumption or the timeslot with the biggest energy generation. In our algorithm, the best placement is threefold: (a) cheapest place according the cost-function, (b) place with the lowest resulting fluctuation of the load profile and (c) no new peak is created. An advantage of our approach is that the functionality remains more or less the same compared to the classic greedy, only the identification of the best placement changes. The greedy pseudocode for solving our algorithm is shown in Table I.

TABLE I. GREEDY PSEUDOCODE

Start	Take maximum/minimum load		
02		Search the cheapest place for the load	
03			Calculate consumption – generation
04			Find lowest result
05		Place the load at this place	
End	Take the next load and start again		

V. ANALYSIS

The analysis should provide two outcomes: first, the algorithm's success in finding a solution and its runtime. Because we have a solution strategy—here a greedy heuristic—and an algorithm that places the load, we need to look at both parts of our solving strategy. We can state, that the

Greedy heuristic will achieve a result, as we just have to sort the amount of shiftable loads and place them afterwards till they are all set. Next, our algorithm focuses each possible timeslot and calculates the costs. Afterwards, the time with the lowest costs is selected. Accordingly, we argue that the termination is guaranteed, as a timeslot can be identified. The runtime is a little more complex. We need to sort n loads—thus, we have an average runtime of $O(n\cdot\log(n))$ and $O(n^2)$ in the worst case, for example, with quicksort. Moreover, our placement algorithm needs to look at m timeslots and calculate the costs for each the runtime therefore is $O(n\cdot m)$. The overall runtime is then $O(m+n\cdot\log(n))$ for the average case and $O(n\cdot m+n^2)$ for the worst case. As we can expect the average case most likely or we can obligate the users to deliver the loads pre-sorted, we can be relatively sure to get an average case. As we are in the AE setting, which means the application area is more important than the worst case, we can guarantee a performance of $O(n\cdot m+n\cdot\log(n))=O(n\cdot(m+\log(n)))$. Following our research methodology, the analysis is an evaluation of the first step according to the functionality and runtime. We can now state, that both can be guaranteed.

VI. CONCLUSION

A. Contribution

In this article we discuss, that in the DR field a multiple objective optimization is valuable and useful. Hence, a new multi-objective optimization problem and a possible solving strategy for the non-linear problem (CMOP) is formulated and suitable factors for consideration in the CMOP are derived. The overall runtime is $O(n\cdot(m+\log(n)))$.

B. Limitations

First, we cannot be sure, that we found all relevant factors to answer the question sufficiently. However, even if a new factor has to be taken into account, the optimization problem and the cost function can be enhanced. Second, we cannot assure that neither the formulated optimization problem nor the solving strategy with a greedy heuristic is the best or optimal solution. As we did not state to formulate or find the best performing solution, but a first iteration towards this, we assume the research question answered (to this point).

C. Further Research

In further steps of our research, we particularly (1) implement the proposed algorithm and (2) carry out various experiments for evaluation. For creating an easy to use library for different strategies, we plan to program the algorithm in JAVA and deploy an API. The implementation phase includes that the following parameters need to be filled with values:

- How much should the cost factor raised, when the actual placement deviates too much from the mean?
- How much deviation from the mean is too much?
- If a new peak is created, how much should the cost factor increase?

As a follow up step, we plan to evaluate the algorithm with an experiment. Therefore, appropriate data has to be selected and prepared. Recorded data from naturalistic living units (analyzed for example in [39, 40]) or artificial data, which has a sufficient quality [41, 42] is possible. In the naturalistic data case, we have to add additional information to the data, for example, the time of usage. For generating artificial data, the LoadProfileGenerator (LPG) [43] can be used, since it has predefined load profiles and uses a behavior model for each user in a living unit to simulate the data. We already conducted first simulations with single households as well as with different combinations in a microgrid. The runtime was as expected. Moreover, the received results indicated, that we achieved the same or nearly the same cost-savings compared to a cost-only-objective algorithm. However, we achieved a better load flattening and peak load reduction compared the status quo (no DR) on the one side and the cost-only algorithm on the other side, but, neither the load profile flattening nor the peak load reduction was as good as that of a convex cost algorithm which was our aim in the first place. Nevertheless we reached (nearly) the same amount of cost savings while the load profile flattening and peak load reduction were achieved as well in these early stage simulations.

REFERENCES

[1] T. M. Lawrence, R. T. Watson, M. -C. Boudreau, J. Mohammadpour, "Data Flow Requirements for Integrating Smart Buildings and a Smart Grid through Model Predictive Control", Procedia Engineering, vol. 180, pp. 1402–1412, 2017

[2] S. Seidel, J. C. Recker, J. vom Brocke, "Sensemaking and Sustainable Practicing: Functional Affordances of Information Systems in Green Transformations", Management Information Systems Quarterly, Vol. 37, No. 4, pp. 1275–1299,. 2013

[3] Q. Hu, F. Li, "Hardware Design of Smart Home Energy Management System With Dynamic Price Response", IEEE Transactions on Smart Grid, Vol. 4, No. 4, pp. 1878–1887, 2013

[4] A. M. Kosek, G. T. Costanzo, H. W. Bindner, O. Gehrke, "An Overview of Demand Side Management Control Schemes for Buildings in Smart Grids", 2013 IEEE International Conference on Smart Energy Grid Engineering, 2013

[5] L. Merkert, I. Harjunkoski, A. Isaksson, S. Saynevirta, A. Saarela, and G. Sand, "Scheduling and energy – Industrial challenges and opportunities", Computers & Chemical Engineering, Vol. 72, , pp. 183–198, 2015

[6] P. Siano, "Demand response and smart grids—A survey", Renewable and Sustainable Energy Reviews, Vol. 30, pp. 461–478, 2014

[7] D. Steen, L. A. Tuan, L. Bertling, "Price-Based Demand-Side Management For Reducing Peak Demand In Electrical Distribution Systems – With Examples From Gothenburg", available at: http://publications.lib.chalmers.se/records/fulltext/163330/local_163330.pdf, 2012

[8] L. Hillemacher, Lastmanagement mittels dynamischer Strompreissignale bei Haushaltskunden (Load management through dynamic price signals), PhD Thesis, Karlsruher Instituts fur Technologie, 2014

[9] A. R. S. Vidal, L. A. A. Jacobs, L. S. Batista, "An evolutionary approach for the demand side management optimization in smart grid", IEEE Symposium on Computational Intelligence Applications in Smart Grid, pp. 1–7, 2014

[10] S. Salinas, M. Li, P. Li, "Multi-Objective Optimal Energy Consumption Scheduling in Smart Grids", IEEE Transactions on Smart Grid, Vol. 4, No. 1, pp. 341–348, 2013

[11] N. Bassamzadeh, R. Ghanem, S. Lu, S. J. Kazemitabar, "Robust scheduling of smart appliances with uncertain electricity prices in a

heterogeneous population", Energy and Buildings, Vol. 84, pp. 537–547, 2014

[12] L. Song, Y. Xiao, M. van der Schaar, "Non-stationary demand side management method for smart grids", IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 7759–7763, 2014

[13] R. Batchu, N. M. Pindoriya, "Residential Demand Response Algorithms: State-of-the-Art, Key Issues and Challenges", International Conference on Wireless and Satellite Systems, pp. 18–32, 2015

[14] Berkeley Lab, "Distributed Energy Resources Customer Adoption Model (DER-CAM) | Building Microgrid", available at: https://building-microgrid.lbl.gov/projects/der-cam

[15] A. Saad Al-Sumaiti, M. H. Ahmed, M. M. A. Salama, "Smart Home Activities: A Literature Review", Electric Power Components and Systems, Vol. 42, No. 3–4, pp. 294–305, 2014

[16] V. S. K. Murthy Balijepalli, V. Pradhan, S. A. Khaparde, R. M. Shereef, "Review of demand response under smart grid paradigm", IEEE PES Innovative Smart Grid Technologies – India, pp. 236–243, 2011

[17] C. Gerwig, D. Behrens, H. Lessing, R. Knackstedt, "Demand Side Management in Residential Contexts - A Literature Review", INFORMATIK 2015. Bonn: Gesellschaft für Informatik, pp. 93–107, 2015

[18] W. Ketter, J. Collins, P. P. Reddy, C. M. Flath, The Power Trading Agent Competition, ERIM, 2011

[19] S. Q. Ali, S. D. Maqbool, T. P. I. Ahamed, N. H. Malik, "Pursuit Algorithm for optimized load scheduling", IEEE International Power Engineering and Optimization Conference, pp. 193–198, 2012

[20] C. Keerthisinghe, G. Verbic, A. C. Chapman, "Evaluation of a multi-stage stochastic optimisation framework for energy management of residential PV-storage systems", Australasian Universities Power Engineering Conference, pp. 1–6, 2014

[21] W. Zhao, P. Cooper, P. Perez, L. Ding, "Cost-Driven Residential Energy Management for Adaption of Smart Grid and Local Power Generation", International Symposium for Next Generation Infrastructure, 2013

[22] Y. Huang, S. Mao, R. M. Nelms, "Smooth electric power scheduling in power distribution networks", IEEE Globecom Workshops, pp. 1469–1473, 2012

[23] P. McNamara, S. McLoone, "Hierarchical Demand Response for Peak Minimization Using Dantzig #x2013;Wolfe Decomposition", IEEE Transactions on Smart Grid, Vol. 6, No. 6, pp. 2807–2815, 2015

[24] R. Verschae, H. Kawashima, T. Kato, T. Matsuyama, "A distributed coordination framework for on-line scheduling and power demand balancing of households communities", European Control Conference, pp. 1655–1662, 2014

[25] F. De Angelis, M. Boaro, D. Fuselli, S. Squartini, F. Piazza, Q. WeiDing Wang, "Optimal Task and Energy Scheduling in Dynamic Residential Scenarios", in Advances in Neural Networks, pp. 650–658, 2012

[26] N. Bassamzadeh, R. Ghanem, S. Lu, S. J. Kazemitabar, "Robust scheduling of smart appliances with uncertain electricity prices in a heterogeneous population", Energy and Buildings, Vol. 84, pp. 537–547, 2014

[27] S. -J. Kim, G. B. Giannakis, "Efficient and scalable demand response for the smart power grid", 4th IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing, pp. 109–112, 2011

[28] L. Song, Y. Xiao, M. van der Schaar, "Non-stationary demand side management method for smart grids", IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 7759–7763, 2014

[29] T. Cortes-Arcos, J. L. Bernal-Agustín, R. Dufo-Lopez, J. M. Lujano-Rojas, J. Contreras, "Multi-objective demand response to real-time prices (RTP) using a task scheduling methodology", Energy, Vol. 138, pp. 19–31, 2017

[30] D. Behrens, T. Schoormann, R. Knackstedt, "Towards a Taxonomy of Constraints in Demand-Side-Management-Methods for a Residential Context", 20th International Conference on Business Information Systems, pp. 283-295, 2017

[31] D. Behrens, C. Ruether, T. Schoormann, K. Ambrosi, R. Knackstedt, "Effects of Constraints in Residential Demand-Side-Management Algorithms - A Simulation-based Study", International Conference on Operation Research, 2017

[32] A. R. Hevner, S. T. March, J. Park, S. Ram, "Design Science in Information Systems Research", Management Information Systems Quarterly, Vol. 28, No. 1, pp. 75–105, 2004

[33] P. Sanders, "Algorithm Engineering – An Attempt at a Definition", in: Efficient Algorithms, Springer, pp. 321–340, 2009

[34] W. Ketter, M. Peters, J. Collins, A. Gupta, "Competitive Benchmarking: An IS Research Approach to Address Wicked Problems with Big Data and Analytics", Management Information Systems Quarterly, Vol. 40, No. 4, pp. 1057–1080, 2016

[35] K. Fuller, R. Ramanath, M. Bohm, H. Krcmar, "Decision Support for the Selection of Appropriate Customer Integration Methods", 12th International Conference on Wirtschaftsinformatik, pp. 1360-1374, 2015

[36] A. -H. Mohsenian-Rad, V. W. Wong, J. Jatskevich, R. Schober, A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid", IEEE Transactions on Smart Grid, Vol. 1, No. 3, pp. 320–331, 2010

[37] J. A. Nelder, R. Mead, "A Simplex Method for Function Minimization", The Computer Journal, Vol. 7, No. 4, pp. 308–313, 1965

[38] A. H. Land, A. G. Doig, "An Automatic Method of Solving Discrete Programming Problems", Econometrica, Vol. 28, No. 3, pp. 497–520, 1960

[39] A. Monacchi, D. Egarter, W. Elmenreich, S. D' Alessandro, A. M. Tonello, "GREEND: An Energy Consumption Dataset of Households in Italy and Austria", IEEE International Conference on Smart Grid Communications, pp. 511-516, 2014

[40] D. Behrens, T. Schoormann, R. Knackstedt, "Datensets für Demand-Side-Management–Literatur-Review-Basierte Analyse und Forschungsagenda" (Datasets for demand side management – Literature review based analysis and research agenda), in Lecture Notes in Informatics, 2016

[41] H. A. Cao, C. Beckel, T. Staake, "Are domestic load profiles stable over time? An attempt to identify target households for demand side management campaigns", 39th Annual Conference of the IEEE Industrial Electronics Society, pp. 4733–4738, 2013

[42] G. Hoogsteen, A. Molderink, J. L. Hurink, G. J. M. Smit, "Generation of flexible domestic load profiles to evaluate Demand Side Management approaches", IEEE International Energy Conference, pp. 1–6, 2016

[43] N. Pflugradt, Load Profile Generator, available at: www.loadprofilegenerator.de