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Demand Side Management in Residential Contexts – A Literature Review

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Abstract: The digitalization in the energy sector offers a great potential to implement Demand Side Management (DSM) in residential buildings and to exploit the flexibility on the side of the consumers. With the possibility to shift energy loads, it becomes easier to use renewable energies efficiently. The increasing number of home devices which can be controlled and the increasing number of electric cars are favorable conditions to implement DSM. This paper provides an overview of the state of the art approaches for DSM in residential contexts. Therefore, a structured literature review is carried out. Thereby, 598 articles are analyzed and categorized via a concept matrix. The results of the existing approaches are examined and it is pointed out in which areas further research is needed. This regards inter alia the need for a publicly available reference data set which would allow scientific benchmarking.

Keywords: Demand Side Management, Demand Response, Literatur Review, Load Shifting, Micro Grid, Smart Grid

1 Motivation

Demand Side Management (DSM) is the concept of shifting demand in order to achieve a balanced utilization in energy grids. This concept exists since the 1980s (cf. [Ge85]). Now it has become increasingly popular due to the integration of renewable energies in the energy systems. The energy production of these is not controllable but depends on external factors like the solar radiation or wind force. In contrast, the demand of many appliances like a dishwasher is flexible and can be shifted within a determined scope. The goal of DSM is to shift load from times in which the energy demand is high to times in which the demand is low or energy can purchased for a favorable price.

DSM becomes feasible due to the integration of information and communications technologies in energy grids. With an increasing number of smart meters[2] in residential buildings it is not restricted to industrial contexts anymore, but a new potential for load shifting in residential contexts emerges. This relative new aspect of DSM is supported by the increasing possibilities of connecting devices and services in the home environment. Another important driver are electric vehicles. The growing number of plug-in hybrid electric vehicles (PHEVs) and electric vehicles (EVs) arises a new potential for load shifting. It can be assumed, that users won't mind at which hour at night the car is charged as long it is ready for takeoff in the morning.

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[2] In Germany the installation of smart meters in new buildings has been forced since 2010 by law, cf. 21b Abs. 3a EnWG

To apply DSM in residential buildings, different approaches have been developed. They differ in the physical framework in which DSM is embedded, in the components which are optimized and in the optimization algorithm itself. Not all of the approaches can be embedded into every framework and not all of the optimization methods can consider every component. To get an overview of the approaches, a structured literature review is required. Thereby, it should be pointed out which methods are used in which framework and which results can be achieved. In doing so, it can be identified, which the next steps are for bringing DSM in residential contexts forward. The guiding research questions are:

- What methods are used for DSM in residential contexts?
- Which framework is chosen for this?
- Which components are integrated?
- What are the comparable results?
- What datasets are used for the evaluation?

2 Research Design

To answer the raised research questions, a structuring framework for a review according to [WW02] is used. This includes a specification of a search string, the choice of suitable databases and an evaluation method. Thereby we follow the concept of [Br09] and construct a concept matrix in order to categorize the results.

2.1 Search String

Firstly, the term “Demand Side Management” is part of the search string. It is complemented by “Demand Response”, which is sometimes used as synonym. As the research focus is on DSM methods in residential contexts, the terms “residential” and ”optimization” are added. The search string is formulated in English as it is the established scientific language. Additionally, it is complemented by the German terms.

A first query on Google Scholar results in more than 6000 articles. Many of them deal with DSM in the fields of water and gas or with the trading of electricity. As these articles are not in in the scope of the research question, they are excluded by adding the following words to the search string:

- water - stock - gas - market - wasser - börse - markt.

In the final search string the single strings were combined with AND connectors:

“Demand Side Management” OR “Demand Response” OR “Demand - Side - Management” OR “Lastverschiebung”) AND (“Optimization” OR “Optimierung”) AND (“residential” OR “Wohn*”) - water - wasser - börse - stock - gas - markt - market

2.2 Databases

One database suitable for the scope of this literature review is the electronic Library AISeL[3], which is a central repository for scientific research in the field of information systems. Furthermore, most research papers are trackable by Google Scholar[4]. Thus, it is used as well. The search is restricted to the time range 2010 –2015 as smart meters for residential buildings have been introduced to the market about 2010.

2.3 Evaluation Method

The articles found are evaluated stepwise by the title, the abstract and finally by the whole article. In this process, all articles are sorted out, which cannot contribute to the research questions. As relevant identified articles are evaluated and categorized via concept matrix. As a result, the different approaches can be compared more easily.

3 Concept Matrix

To classify the articles found systematically, a concept matrix is developed (cf. [Br09]). Therefore, the dimensions are determined by the research questions. One dimension is the physical *framework* in which a proposed method is embedded. One dimension are the *optimization methods*. For the evaluation of the methods, it is important to know which components are optimized and which assumptions are used for the databasis. These questions are captured in two more dimensions: *components* and *data basis*. The dimensions are visualized in figure 1.

3.1 Framework

There are different frameworks to control and motivate load shifting in residential buildings. A rough division can be made between locally controlled DSM and centralized controlled DSM. Moreover there are hybrid forms, in which a hierarchical structure of the smart grid is supposed. Another broad division concerns the communication, which can be one-way or bidirectional. Optionally, DSM can be performed automatically and/or manually. To develop a stringent but clear classification, four categories are used to cover the possible frameworks concerning DSM for residential loads.

The first category is *centralized controlled DSM*, which means that the deferrable loads of several households and/or EVs are controlled by one central node. This category includes the central management of several households and/or charging stations up to whole cities. Furthermore, the central node can be part of a larger hierarchical system. There has to be a bidirectional communication between the deferrable load and the controlling node.

[3] http://aisel.aisnet.org/
[4] http://scholar.google.de/

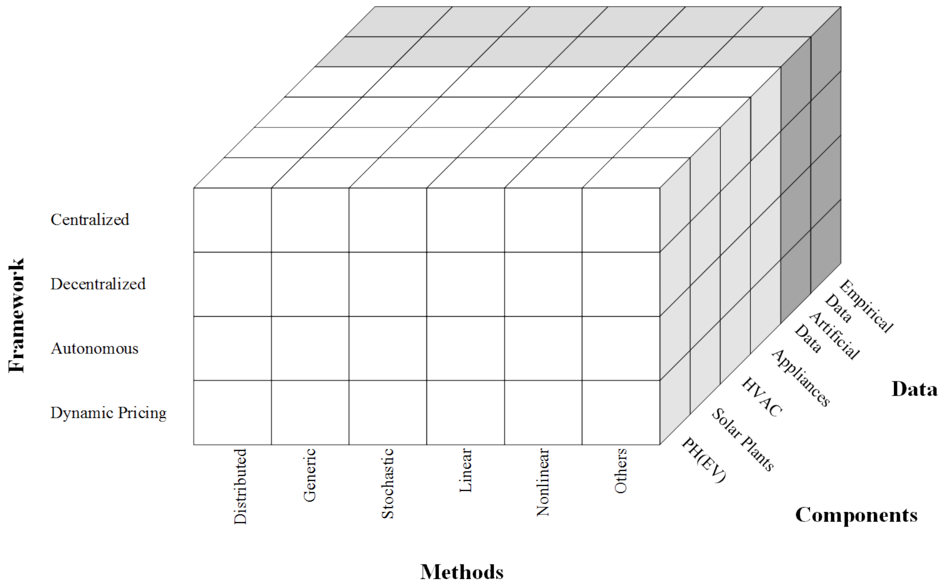

Fig. 1: Dimensions of the Concept Matrix

The second category is *distributed coordination of DSM*. In this scenario several households and/or charging stations communicate in a bi- or multidirectional manner to establish an optimal scheduling plan to match their demands.

Another approach is *autonomous DSM for one individual household*, possibly with one EV. The optimization problem only concerns the energy management of one household and one charging station. The goals are to increase the level of captive use, if a solar plant is installed, and/or to lower the energy bill by shifting loads to more favorable times. This approach can be combined with methods of the next category, which proposes variable energy prices as incentive for load shifting.

The last categoriy is *Dynamic Pricing*. The goal is not to control deferrable loads, but to motivate consumers to shift their load manually or to trigger smart devices by implementing variable electricity prices. In the process new peaks of energy demand have to avoided. The communication network is solely a one-way communication medium, through which the electricity prices are communicated.

3.2 Methods

In all cases a mathematical optimization problem has to be solved. There are many methods which can be applied. Considering the complex framework, heuristic methods in the fields of *genetic algorithms* and *stochastic optimization* can be expected, whereas *distributed algorithms* can support the distributed structure of the deferrable loads. Obviously, standard solvers of the fields of mixed integer *linear* and *nonlinear programming* can also be expected.

3.3 Components

To get an overview, which methods can deal with which components, it is distinguished between four groups of components. The first one are *household appliances* which have a fixed load profile. Only the starting point is flexible. These appliances could be dish washers, washing machines, dryers etc. The second group describes *thermic loads* like heating and air conditioning (*HVAC*). They are characterized by the goal to reach or to hold a certain temperature. In doing so, energy is needed in more or less cyclic terms. The third group of consumer are *electric vehicles or plug–in electric vehicles*. In the charging process a certain amount of energy is needed. The electrical power can vary within certain bounds. Further components, which can optionally be considered, are *solar plants*. The energy production of these is not controllable, but it can be included in the constraints of the optimization problem.

3.4 Data Basis

In order to compare the results of the articles, it is important to have a look into the data sets used for evaluation. Thus it is reviewed, if they are *empirically obtained* or *artificially created*.

4 Results

4.1 Classification in the Concept Matrix

The keyword-based search leads to 598 articles[5]. A huge amount of articles could be sorted out by reading the titles and abstracts. These were for example articles about the management of storages, about DSM in commercial and industrial contexts or about the infrastructure without any optimization method. The remaining 55 articles[6] have been evaluated by reading the whole articles carefully. Thereby, 48 articles have been identified as relevant and have been categorized via the concept matrix (s. table 1). The evaluation is done stepwise for each framework. A comparison of the evaluations done in the papers is presented in the next subchapter. It is followed by the conclusions and limitations.

[5] The search was conducted between 23^{th} and 28^{th} December 2014

[6] For 5 articles, it has not been possible to organize the full version. These have been categorized by reading the abstract. They are marked with a *.

References	Framework				Methods						Components				Data	
	centralized	decentralized	autonomous	Dynamic Pr.	distributed	genetic	stochastic	linear	nonlinear	others	appliances	HVAC	solar plants	(PH)EV	empirical	artificial
[ASHK13]			X					X			X					X
[Al12]			X							X	X					X
[Al13]			X	X						X						X
[DA12]			X					X			X					X
[At13]			X							X	X					X
[AYK14]				X			X									
[Ba14]			X				X				X				X	
[BF13]	X								X					X	X	
[BLH12]		X			X									X		X
[BN14]			X							X	X				X	
[CC11]			X					X			X		X			X
[Ch13]		X			X									X		X
[Co14]	X							X							X	
[CYN14]		X			X					X	X			X		X
[Du13]		X						X						X	X	X
[Fe12]	X								X		X	X		X		X
[FG12]		X	X				X							X		X
[HMN12]		X							X		X					X
[Hu14]			X				X				X					X
[Ji11]			X				X				X	X		X		X
[KG11]			X							X	X					X
[Li14a]*			X			X					X					
[Kw12]		X					X					X			X	
[LF14]			X				X				X		X			X
[Li14b]			X				X				X					X
[LP13]			X			X					X					X
[LPK12]			X			X								X		X
[Ma14a]		X			X						X			X		X
[Ma12]			X							X						X
[Ma14b]*			X						X		X	X				X
[Me10]	X		X						X					X		X
[MH14]	X								X					X		X
[MHC12]			X			X					X					
[MM13]		X			X						X	X		X		X
[Mi11]			X					X				X	X			X
[Pe13]			X							X	X	X				X
[RZ15]*			X			X					X	X				
[Sa10]		X			X						X					X

References	Framework				Methods						Components				Data	
	centralized	decentralized	autonomous	Dynamic Pr.	distributed	genetic	stochastic	linear	nonlinear	others	appliances	HVAC	solar plants	(PH)EV	empirical	artificial
[SLG14]		X			X									X		X
[SXvdS14]	X				X			X								X
[St15]*			X							X						X
[Ta13]*	X					X								X		X
[DVF13]	X									X	X					X
[Ve14]		X					X							X		
[YTN12]				X	X											X
[Za13]	X						X				X					X
[ZBG12]*	X					X					X	X				
[Zh13]	X					X					X	X	X			
Summe	**11**	**12**	**25**	**3**	**9**	**8**	**9**	**8**	**6**	**10**	**26**	**11**	**4**	**16**	**6**	**36**

Tab. 1: Concept Matrx augemented with references

4.2 Evaluation of Concept Matrix

Autonomous DSM for one Individual Household

A large proportion (25 of 48) of the articles deals with autonomous DSM for individual households. Thereby, genetic algorithms, stochastic optimization and linear programming are each proposed by 20% of the articles. Further methods are pursuit algorithms ([Al12], [Ma12]), Multi-Objective-Programming [BN14], Fuzzy Clustering [Pe13], combinatorial mathematics [Al13] and Dynamic Programming [KG11].

Six articles consider thermic loads, which increase the complexity of the optimization problem. In [Ma14b] and [Mi11] these loads are modeled by non-linear constraints. [Ji11] uses a stochastic differential equation and optimizes the expected value. In [At13], a thermal energetic building simulation is used to generate training data for a neural network. It learns to keep the temperature. Three articles [CC11], [LF14], [Mi11] optimize the captive use of solar plants on the rooftop. Thereby, [LF14] takes the uncertainties in supply and generation into account by using confidence intervals.

Decentralized Organized DSM

Decentralized organized DSM is examined by 12 articles. Thereby, eight articles are built up on the model of Mohsenian-Rad et al. [MR10], in which distributed agents find the unique Nash-equilibrium by using best-response-algorithms. The equilibrium is equivalent to the global solution of the optimization problem, if certain conditions are met. In [Ma14a] and [SLG14] the model is extended by integrating energy storages. [Sa10] adapts the model for Real-Time-Pricing instead of determined cost functions. In this article and in [Ch13] the iterations of the distributed algorithm are not performed sequentially, but simultaneously in order to speed up the calculation time. The approach of [CYN14] is based on game-theoretical considerations as well. To guarantee the convergence of the algorithm, a penalty term is used for changes of the scheduling plan. [BLH12] extends the model by adapting the constraints for EVs and by considering physical constraints of the energy grid. The problem of not knowing the constraining parameters of the optimization problem 24h in advance is addressed in [FG12]. Therefore, random variables are used. In [MM13] it is proven, that their proposed algorithm, which uses a division of the optimization problem, is three times faster than a centralized approach.

In [HMN12] priorities are assigned to the loads. The optimization problem is then solved by a distributed algorithm. [Ve14] models the optimization problem with Markov processes and thus the model can handle uncertainties. In [Du13] reinforcement learning is used to organize the charging process of EVs.

Thermic loads are only modeled by [Kw12] in contrary to electric vehicles, which are considered in the constraints by 9 of 12 articles.

Centralized Organized DSM

In the review process 11 articles are identified, which assign the management of residential loads to one central coordination point which coordinates more than one household. Four articles ([BF13], [Me10], [MH14], [Fe12]) apply nonlinear programming to solve the resulting complex optimization problem. Three articles favor genetic algorithms like [Zh13], [Ta13], [ZBG12]. In [Za13], there is a central agent, which calculates the load shifting by a fuzzy Markov game and simulated annealing. The actions of the consumers are captured by Q-Learning. In [SXvdS14] the optimization problem is modeled as game, in which a central node calculates the best actions for the other nodes, which represent appliances. [DVF13] optimizes HVAC systems with the scheduling algorithm Earliest Deadline First.

Half of the methods concentrate on (PH)EVs. To optimize the charging process [Zh13] uses a genetic algorithm, in [Ta13] the optimization uses an Estimation Distribution Algorithm. [BF13] puts up a quadratic optimization problem in which the size of the battery, the loading capacity and the current energy prices are considered. The evaluation is performed on the National Household Travel Survey (NHTS). [MH14] develops an online application which coordinates the charging process of electric vehicles.

Dynamic Pricing

Dynamic Pricing is an important aspect for DSM as many approaches react on price incentives. Variable energy tariffs are often part of the constraints for the optimization problem. Nevertheless, it is usually examined in larger context and does not focus on individual residential households. Furthermore, some papers may be not found by the keyword-search as the term ”market” is excluded. As a result there are only three articles about the design of dynamic energy prices found in the selection.

In [YTN12] the scheduling task is modelled as non-cooperative game. Assuming that consumers choose the action, which is most profitable for them, the energy prices are calculated which lead to the most balanced load distribution. In [AYK14] the energy prices are determined one hour ahead by looking into the predicted loads and the probability of consumers reacting on price changes. [Al13] proposes a tariff which does not only change in time, but considers the maximal demand of the day in the billing process. In doing so, new load peaks as reaction to low prices can be avoided.

It is not specified, which deferrable loads are modeled in these approaches as it is the choice of the consumers. Nevertheless, concerning a simulation it would be important to model a realistic scenario.

4.3 Comparison of the Evaluations and Data Sets

Nearly all (41 of 48) articles provide simulation results to their approaches. About 70% of the articles generate artificial data sets. For example [SXvdS14] uses standard load profiles to simulate the load distribution for ten households. Thereby, 40% of the load is assumed to be flexible. In [Sa10] the demand of 250 households is modeled with a random distribution and it is assumed, that 50% of the loads are flexible. In [Ve14] the charging processes of 20 EVs at 20 households are modeled. Thereby, different percentages (15%, 30%, 45%) of flexible households are tested. The constraints are modelled by Gaussian distributions. In [LP13], [CC11] and [Ji11], the simulations only include deferrable loads. In [LP13], these loads are modeled with an inflexible load profile, which is simulated by a random distribution. In [CC11], a dish washer, a washing machine and a dryer are modelled in detail. Similar approaches have been used for the other articles with a artificially generated data set.

Six articles refer to empirically recorded data sets: In [Du13] the Irish Smart Metering Data from the Commission for Energy Regulation ([CE15] is used to simulate an optimal charging management of nine EVs connected to nine households. The evaluation of [Ba14] also derives the constraining parameter by using Smart Metering Data. It uses the Olympic Peninsula Demonstration Testbed [Ch10]. [BN14] applies the real energy prices which were charged in Long Island of New York 2013 [Ne13] to simulate the optimal usage of three household appliances (dishwasher, washing machine and dryer). A similar evaluation method is used in [Kw12]. Therefore, the total consumption of the University of Southern California as well as the consumption of single appliances like the HVAC, light and laptops were measured. Based on this, load shifting could then be simulated for a relatively realistic scenario. [BF13] looks into the charging management of EVs and uses the U.S. National Household Travel Survey Dataset [20] to simulate usage patterns. For [Co14] a field trial was carried out, in which 10 households took part in. The users specified, in which time frames they would like to do their laundry seven days ahead. A central node calculated the optimal starting points and informed the users via SMS.

The goal of the presented approaches is to reduce peaks in consumption or to adapt the consumption in accordance to a cost function. Thereby, a cost reduction of about 20 – 75% is achieved. However, the results are not comparable as different assumptions are made. This not only includes the cost functions but also the uncertainty of the forecasted loads, the number of updates used for one day, the modeling of the constraining parameters and the percentage rate of flexible loads in the total consumption.

4.4 Conclusions

Particular emphasis of the research done so far is placed on autonomous DSM. The approach benefits from independence to other households. The optimization problem is limited to a manageable amount of appliances, which are partially modeled in detail. There are various optimization methods which can cope with this kind of problems. The communication infrastructure can be relatively simple as in most cases the only information which has to be communicated are the energy tariffs for the next 24 hours. However, the independence to other households has its drawbacks. Usually, the best solution for a local network load cannot be reached this way. Decentralized DSM pursuits this and allows negotiations of several households. By doing this, the number of degrees of freedom is increased and the parameters are connected to each other, so that a generation of new peaks can be avoided. Under certain conditions, a global optimum can be reached that way as [MR10] proves by applying game-theoretical theorems. Most of the research found for decentralized DSM relies on the model of [MR10] and tries to enhance the approach in certain aspects.

Given that all constraining parameters are known, a centrally organized DSM can find to the optimal solution. For example, in [Me10] a centralized strategy for charging EVs is compared to a local one, in which a charging process is controlled by the smart home management of one individual household. Thereby, the decentralized strategy reaches slightly better results, but it also requires a more complex communication infrastructure. The need of a multi-directional communication infrastructure is a drawback for all approach of DSM which include more than one household. Additionally, questions of data protection turn up as sensitive data is exchanged between the different participants. This might be the reason why 5 of 10 articles dealing with the optimization of EV charging concentrate on public stations. In this context, the question of data privacy is not as critical as in the private context.

In the evaluation of the methods proposed in the articles, crucial short-comings are revealed. The data sets used for the evaluations are often based on highly simplified assumptions and can therefore only be used for feasibility tests of the algorithms. To carry out scientific benchmarking publicly available data sets are needed which are measured empirically and in which deferrable loads are marked. Furthermore, it would be useful to know how long in advance the deferrable loads are reported.

Besides real data sets used for evaluation in [Du13] and [Ba14], data sets of Non-Intrusive-Appliance-Load-Monitoring (NIALM) can be recommended. There is for example the AMPds dataset ([Ma13]) in which the demand of each component is stated individually.

4.5 Limitations

The keyword search cannot guarantee that all articles related to DSM in residential context are found. To the contrary, some relevant articles are missing for sure. However, the present literature review gives a comprehensive overview of the methods and algorithms used in the residential context of DSM. In addition to that, short-comings and open questions are pointed out.

5 Summary and Outlook

The literature review clearly shows that the implementation of DSM in a residential context is a current research topic in which various different approaches are tested. By categorizing the articles for DSM in different dimensions, it can be seen which approaches work for which frameworks, for which components and with which optimization algorithms. The analysis of the evaluations done in the articles reveals a lack of empirically measured and publicly available data sets and an agreement on error measure to compare the performance of the algorithms.

Some articles take up the fact, that the input parameters of the assumed demand can only be random variables. It seems that further research is needed to cope with this fact. Additionally, it is not fully modelled yet, that deferrable loads are not known 24h ahead, but only reported during the day. Thus, there is a research gap concerning the explicit consideration of uncertainties and a continuously adaptation of the demand scheduling during the day.

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