Residential Demand Response Algorithms: State-of-the-Art, Key Issues and Challenges

Rajasekhar Batchu and Naran M. Pindoriya(✉)

Electrical Engineering, Indian Institute of Technology Gandhinagar,
Ahmedabad 382424, Gujarat, India
{batchu.rajasekhar,naran}@iitgn.ac.in

Abstract. Demand Response (DR) in residential sector is considered to play a key role in the smart grid framework because of its disproportionate amount of peak energy use and massive integration of distributed local renewable energy generation in conjunction with battery storage devices. In this paper, first a quick overview about residential demand response and its optimization model at single home and multi-home level is presented. Then a description of state-of-the-art optimization methods addressing different aspects of residential DR algorithms such as optimization of schedules for local RE based generation dispatch, battery storage utilization and appliances consumption by considering both cost and comfort, parameters uncertainty modeling, physical based dynamic consumption modeling of various appliances power consumption at single home and aggregated homes/community level are presented. The key issues along with their challenges and opportunities for residential demand response implementation and further research directions are highlighted.

Keywords: Demand response · Distribution grid · Home energy management system · Price-based programs · Renewable generation · Battery storage · Load scheduling

1 Introduction

Deployment of smart grid technologies and integration of information and communication infrastructure in the existing electricity grid has brought immense automation, control and visualization in the grid. With the advent of ubiquitous data networks and advanced metering infrastructure (AMI) that enables bi-directional communication, the demand side energy management (DSM) has now attained an intelligent outlook in the smart grid framework. DSM is the cost-effective tool to intelligently control the customers' load demand; in general, it focuses on load shaping i.e. modifying the energy consumption pattern of users over time and at the same time improves service quality and customer satisfaction. Major thrust areas of DSM are: (1) demand response (DR) - an approach to reduce customers' consumption by shifting, shaving and shaping the electricity load in response to a peak energy signal from the power utility and (2) energy efficiency and energy conservation programs. Appropriate load-shifting is foreseen to be even more crucial with increasing penetration of distributed generation like roof-top solar photovoltaic (PV) in conjunction with/without battery energy storage

P. Pillai et al. (Eds.): WiSATS 2015, LNICST 154, pp. 18–32, 2015.
DOI: 10.1007/978-3-319-25479-1_2

system (BESS), plug-in hybrid electric vehicles (PHEV), power intensive HVAC loads and usage of intelligent appliances, making the customer load profile more stochastic.

Therefore, intelligent DSM algorithm to reduce peak load and manage the satisfactory quality of power has gained a lot of attention at the customer segment in the distribution network. Though, very limited papers [1, 2] that summarize the DSM algorithms and relevant technical challenges broadly in smart grid available in the literature, however, it is found that few recent residential DR algorithms covering state-of-the-art, key issues and research challenges are not properly highlighted. Therefore, this paper solely focuses on DR algorithms for residential customers at individual and multi-user levels (community segment) and highlights their benefits and challenges in effective design and implementation. The rest of the paper is organized as follows. Section 2 provides a background of the different scenarios of the problem. Section 3 provides a quick glance of optimization model used to describe the problem. Section 4 reviews important and recent DSM mechanisms individual and group of cooperative/competitive consumers. Finally, Sect. 6 provides identified challenges and opportunities for future research.

2 Residential Demand Response and Home Energy Management

A typical smart home consists of various types of power appliances, local renewable energy generation (such as rooftop solar PV, small wind turbine) with/without a battery energy storage, and an electric vehicle (EV) networked together to a home energy management system (HEMS) which is real enabler of residential demand management. HEMS is the key element comprises of a desktop or an embedded system that runs GUI monitoring software applications, as well as a communication technologies like ZigBee, Wi-Fi, etc. It is also to be noted that HEMS should have machine learning, pattern recognition, prediction capabilities and interface with the user [3] and demand response aggregator/community EMS. Loads in the residential sector are classified by EPRI's load database used by National Energy Modeling System (NEMS) into nine types viz. space cooling, space heating, water heating, cloth drying, cooking, refrigeration, freezer, lighting, others [4]. Based on their demand management potential, these are classified as critical loads - which might affect the day to day life of consumers when controlled. On the other hand, loads which do not have a major impact on consumer lifestyle are treated as controllable. Demand Response (DR) is effective mechanism which can provide residential consumers with an opportunity to reduce energy consumption costs and simultaneously help the utility to reduce the peak-to-average ratio (PAR) of power. Apart from peak load management, it provides various other applications and benefits like context-aware, power saving services, automation services, etc.

Depending on the price-scheme used, some DR programs may operate in real-time, whereas others may work on a day/hour ahead scheduling basis. The most general DR algorithm is typically formulated as an optimization problem that helps to minimize the cost of consumption of electricity on the customer side or maximize the profit on the utility side. Subject to a set of operating constraints like user comfort levels, priority and operating patterns of appliances, weather conditions, etc., and data uncertainty and user behavior considerations as shown in Fig. 1 The formulation of the algorithm and the load control strategy depends on the type of loads, typical usage patterns, working cycles, uncertainty considerations, behavior modeling, technical constraints and distributed renewable generation and storage facilities available, etc., Hence, demand response potential of various appliances needs to be assessed for designing a DR algorithm.

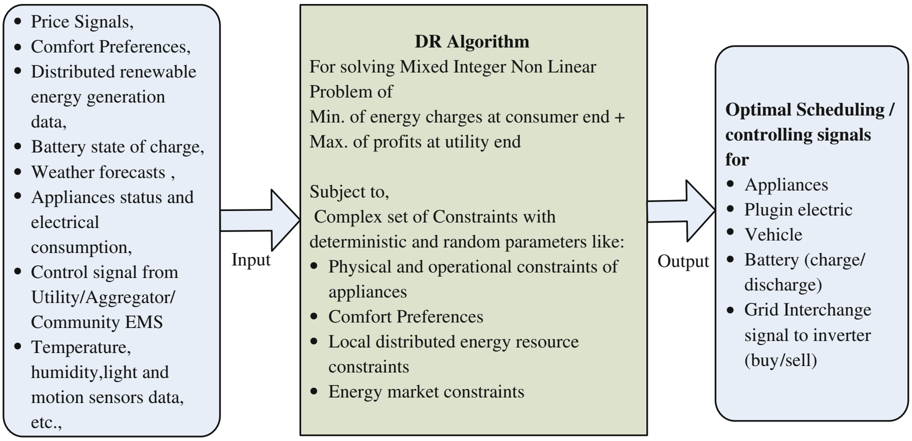

Fig. 1. Inputs and outputs for a typical smart home residential DR algorithm

However individual customer demand control mechanisms will have undesirable effects like peak rebound problem, blackout or brownouts, disturbing the load diversity if not properly coordinated. To avoid these side effects and further benefit the multiple consumers by utilizing the demand diversity and energy resources for grid oriented objectives and cost minimization. These multi customer demand management mechanisms mostly control/coordinate the task scheduling of appliances and dispatch of local distributed energy resources of customers community. This kind of scenario requires a distributed architecture with robust and generic model in order to handle the system complexity. Hence either coordinative multi-agent based optimization techniques or by competitive game-theoretic methods are used which are supervised by an aggregator/community EMS.

3 Demand Response Optimization Model: Mathematical Framework

A typical residential demand management is a mixed-integer non-linear programing problem with characteristics of stochastic, dynamic, multi-objective and multi-actor. Based on the types of loads, and pricing schemes and nature of decision variables involved, and the ability to include uncertainties, scalability, responsiveness, communication requirements, various mathematical formulations and optimization techniques have been suggested for DR management. In this section, a comprehensive description about the optimization model for individual home case and group of homes case related to a day ahead scheduling scenario is provided. Also a brief description about how they can be extended to real-time conditions.

3.1 DR Optimization Model: Single Home

Objectives: DR optimization problem is to manage the electrical consumption, generation and storage resources of the customer over a period of time (typically a day) divided into time slots of a few minutes to the extent of an hour. The objectives could be:

1. Minimize the total electricity cost, usage cycle cost of the battery storage
2. Minimize the inconvenience experienced by the users for delayed operation of time and power shiftable appliances and thermal discomfort level operation of HVAC loads out of their lower/upper limit of the user's comfort zone.
3. Maximization of local generation and storage resources by self-use (or) buying/selling from/to the grid.
4. Minimization of peak demand and/or peak-to-average ratio (PAR).

The optimization model for above objectives are considered from [2] is given below for ready reference.

$$
\begin{gathered}
\min . \sum_{t \in T}\left(c_t \cdot y_t-d_t \cdot z_t-\left(R_t^U \cdot a_t^U+R_t^L \cdot a_t^L\right)+\left(E_t^{B+} \cdot R_b+E_t^{B-} \cdot R_b\right)\right) \\
\min . \sum_{t \in T}\left(\alpha \cdot \sum_{s \in S} f_{st}^S+\beta \cdot \sum_{e \in CB} f_{et}^{CB}\right), \max . \frac{\sum_{t \in T}\left(E_t^{PV}-E_t^{net}\right)}{\mu \cdot E_t^{ToT}} \text { and } \min . \frac{L_{peak}}{L_{avg}}
\end{gathered} \tag{1}
$$

Where c_t, d_t are buying, selling cost of energy and y_t, z_t are energy brought and injected into the grid at time $t \in T . R_t^U, R_t^L$ can be reward paid/penalty collected depending on demand request satisfaction of high and low limits at time $t \in T$ respectively. a_t^U, a_t^L are binary variables indicating the constraint satisfaction. R_b is battery storage system utilization cost per cycle, E_t^{B+}, E_t^{B-} are t is the time slot.α,β are weights and f_{st}^S,f_{et}^{CB} are discomfort associated with shiftable, comfort based appliances respectively. And $E_t^{RES}, E_t^{net}, E_t^{TOT}$ and μ are energy generated, net generation, total demand and energy conversion parameter respectively. And L_{avg} average load demand and L_{peak} is peak load demand.

Constraints: A residential customer has four major types of appliances based on controllability: fixed/critical, time-shiftable, power-shiftable, comfort based and local renewable energy generation and storage devices. The major constraints could be energy balance and equality and inequality constraints of loads. A brief description of the constraints are:

Fixed/Critical Loads: whose power consumption and usage cannot be controlled (refrigeration, lighting, TV etc.).

Time Shiftable: are that can only be shifted in time and operates on its own power consumption pattern (e.g., washing machine, dishwasher).

Power Shiftable: are the appliances which have a prescribed energy requirement depending upon the usage of customer (e.g., pool pump, EV). Their constraint modeling can be found in [5].

Comfort Based: The devices that are used to control a physical variable that influences the user's comfort (e.g., HVAC, water heater). Modeling details are presented in [6].

Local Energy Generation and Storage Systems: The local RE based generators such as PV, micro wind turbine, can be either used locally, stored in a battery or injected into the grid depending the buying and selling pricing [7].

This kind of day ahead model's tentative scheduling is extended to real time by a second stage short term stochastic programing problem for optimal scheduling and control; where the time interval is typical a few minutes for considering demand response signal and the uncertainties in price, load demand and local generation forecast etc., with receding time interval. A multi time scale model predictive approach for stochastic modeling is presented in [8].

3.2 DR Optimization Model: Community Level/Aggregated Customer Level

In this case, a community of residential user's will cooperate/negotiate with Aggregator/Community energy management system (CEMS) in managing the power exchange with the grid. The goal of a typical coordinated model is to minimize the global daily energy bill of the group of users by scheduling the users with in their allowable time limits.

$$\min \sum_{u \in U} \sum_{t \in T} \left(c_t . y_t^u - d_t z_t^u \right) \tag{2}$$

The first term is the cost of energy purchase and the second one cost of energy selling. Where y_t^u, z_t^u energy brought and injected into the grid at time $t \in T$ by the user $u \in U$ is total number of users. The constraints could be total peak load of the users cannot exceed global peak power, network operational constraints, etc. the detailed modeling of the constraints can be found in [9].

4 Residential DR Algorithms: State-of-the-Art

A critical review of very recent DR algorithms for residential energy management is presented in this section. The focus is on the works related to single home and multi-home scenarios, their targets and solution techniques used. And how they tackled the challenges related to work like data uncertainty handling, user behavior modeling, customer involvement, pricing scenarios, cases with and without distributed RE based generation considerations. It was expected that the total number of publications would go up to 500 by the end of 2014 [1].

4.1 DR Methods at Individual Home Level

Single user optimization methods are defined to control load and energy resources of customer. Several classical and heuristic algorithms and techniques are proposed for scheduling and control of appliances along with/without distributed energy resources, under day ahead and real-time pricing environments. Genetic Algorithm (GA) is considered in [10] for load scheduling in an environment containing distributed RE based generation with an objective of peak load minimization and compared with mixed integer linear programing (MILP) approach. Along the same lines, an MILP problem formulation is proposed in [11] to minimize electricity cost subjecting to energy phase and operational constraints. In [12] proposed a convex programing (CP) optimization model for and demonstrated its computation complexity reduction capabilities. A multiple knapsack method is proposed (MKP) [13] for optimal load scheduling.

Real time pricing (RTP) is combined with inclining block rate (IBR) model in [14] to address the problem of possibility that most appliances may operate during the time with the lowest electricity price which may damage the entire electricity system due to the high PAR and solved using GA. Authors in [15] developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) enabled Master Controller (MC) for HEM, where MC schedules the appliances as per user desires and communicates the same with the appliance nodes and ANFIS predicts the customer profiles and sends it to an aggregator.

To tackle the problem of uncertainty and randomness in the considered data many stochastic and robust algorithms that are used are: A typical automated optimization based residential load control scheme using RTP combined with IBR is proposed in [16] which predicts the price ahead time interval. An model predictive control (MPC) based appliance scheduling algorithm is proposed in [17] for buildings, for both thermal and non-thermal appliances. Where as in [8], a two timescale based MPC is proposed for DR considering stochastic optimization model. The authors in [18] proposed a control strategy for peak load reduction by adjusting set point temperature of HVAC loads with in customers preferred tolerance levels by comparing the retail price with threshold price level set by consumers. The uncertainty in behavior of consumer appliance usage is addressed by fuzzy-logic approach in [19]. A least square SVM mechanism for predicting load demand is presented in [20].

An integrated planning and controlling approach for optimal energy management in residential areas with RE based generation is proposed in [21]. The problem of renewable source and electricity price variations is addressed in [22, 24] by dynamically allocating different priorities to appliances according to their status and scheduling them according to the predicted output of renewable sources and the electricity market price forecasting. For customers who need to schedule their consumption, generation and storage, in [23] the authors have proposed an optimization algorithm for power scheduling using MILP. A simple and robust optimization technique is proposed in [22] considering uncertainties in price, renewable power generation prediction. A real time DR algorithm for limiting the load based on user comfort levels or priorities of appliances is given in [25] and its hardware demonstration in [26].

The challenge of consider multiple conflicting objectives with a meaningful balance between them, is partially addressed in [27, 27] by proposing a framework and indices for considering cost, user's convenience and comfort as a mixed objective function and demonstrated with a real data based simulation. Whereas [29] has a multi objective optimization along with uncertainties in the input data. Authors in [30] proposed and demonstrated a task scheduling cum energy management strategy for demand response management in a smart home. But these individual control techniques leads to large peaks during low cost periods and causes rebound peak, service interruptions etc., and to address these problems, the control strategies for community level energy management and DR algorithm has been proposed in literature.

4.2 DR Methods at Community Level/Aggregated Homes

Optimization methods for aggregated users are two types: (1) centralized scheduling (optimization approaches) – an extension of single customer methods to multiuser level and (2) distributed scheduling can be competitive or collaborative approaches (Game theoretic approaches) based on load diversity. The problem scenario and the distributed optimization schemes applied are as discussed below.

In [31], an incentive-based consumption scheduling scheme was proposed for multiple users connected to a single source and solved using coordinate ascent method. Game theoretic approaches are given in [32, 33]. Using an optimal stopping approach defined in [34], a real-time distributed scheduling scheme [35] considering randomness in pricing, appliance priority and power constraint to tackle peak load is presented. The optimization model that adapts the hourly load level in response to forecasted hourly electricity prices is presented in [36].

Authors of [9] have proposed two approaches for evaluating the real-time price-based demand response management for residential appliances namely, stochastic optimization and robust optimization. In [37] a scalable and robust Lagrange relaxation approach (LRA) has been proposed for minimizing energy cost and maximizing consumer satisfaction taking into consideration of variations in renewable generation and price uncertainties. An online algorithm, called Lyapunov-based cost minimization algorithm (LA), which jointly considers the energy management and demand response decisions is proposed in [38]. Vickrey–Clarke–Groves (VCG) auction based mechanism for maximizing social welfare of aggregated users is presented in [39].

Authors in [40–42] have proposed a distributed and coordinated control approaches respectively with focus on overcoming the peak rebound problem. On similar grounds in [43] general algebraic modeling (GAMS), in [44] Stackelberg non-cooperative game theory, agent-based model is developed in [45, 46] Q- learning an online reinforcement learning method is proposed for distributed control of time shiftable appliances. Reference [47] focuses on PHEV in which the authors have proposed a distributed algorithm whereas previous works solely dealt with centralized algorithms. In [48] authors proposed two different approaches for residential load scheduling combined with bi-directional energy trading using their EV's.

To tackle the demand uncertainties and randomness in real time environment in [49] DRSim, a physical simulator is proposed, which can be used to analyze algorithms performance at different case studies.

In [50] proposed an enhancement to the decentralized approach for deferrable and thermal loads of large group of customers. It showed that by adjusting to agent's behavior for market prices, by using adaptive Widrow-Hoff learning rule for deferrable load pattern and modeling their thermal load profile variations. Their strategy gives the emergent behavior of a centrally coordinated mechanism. A single approach will not suit for all the needs in [51] a comparison of various coordinated algorithms viz. balancing responsible, round robin, negotiation and centralized algorithms for a community with multiple house agents for appliance scheduling with respect to diversity, participation of community and amount of peak load reduction.

Table 1. DR optimization methods overview

	Individual home level	Aggregated homes level
Typical objectives	Min. of cost/Max. of comfort/Min. of peak load/Max. of self-consumption of local RE generation (or) combination of these.	Min. of cost, Min. of carbon emissions and Max. of social welfare
Typical constraints	Thermostatic and non-thermostatic controlled appliances, BESS, EV and their parameter limits, time & usage limits.	Non-thermostatic controlled appliances, BESS, EV constraints and price & load uncertainties, distribution network operational constraints etc.,
Optimization methods	GA [14, 18], ANFIS [15], CP [12], MPC [17], MILP [11], PSO [54], MKP [13]	GT [32, 33], MILP [33], Stochastic [9], LRA [37], LA [38], GAMS [43], Q-learning [46], Stackelberg GT [47], Heuristic [53], Agent based model [45]
Architecture and components	Single customer with Home energy manager that communicates with utility/aggregator.	Hierarchical architecture with distributed agents (i.e., home energy managers), centralized agent (aggregator or community energy manager)
Benefits and limitations	Self-use of renewable energy, cost and discomfort minimization, Privacy and Limitations are peak rebound, black out.	System wide perspectives, social network based sharing the useful information for mutual benefit. Difficulty in coordination between house agents, dependency on aggregator, privacy issues.
Popular simulation platforms used	PSCAD, MATLAB along with its optimization, fuzzy logic and ANFIS capabilities and solvers like GAMS.	JADE [55], GridLab-D [56], MATLAB environments. Most of the times a combination of these E.g. Agent-based architecture modelling of household devices in MATLAB and agents in JADE [57].

Although a large number of papers are available on DR algorithms for residential consumers, very few [52, 53] have focused on including power generation by addition of RE based generation at single home level and distributed generation (DG) at the community level respectively, considering together with their intermittent nature. This is one of the major challenges in going ahead with smart grid implementation. An overview of individual and multi user level approaches is presented in Table 1.

5 Residential DR: Key Issues, Opportunities and Challenges in Implementation

Based on the above survey, the derived important aspects, identified key issues and challenges for DR optimization methods implementation in residential sector and research directions are:

- Firstly an intelligent HEMS system [58] interconnected with local RE based energy sources, battery storage and loads is required at the consumer end for DR participation. The participation of the user depends on economic DR programs and efficient and secure information tools from the Aggregator or utility.
- Some works focused only on mathematical modeling and solution strategy for case specific simulation studies. Research works considering a realistic problem scenarios and possible problems, potential effects and cost benefit analysis is the further scope for research.
- In single home scenario, as the number of objectives increases, the tradeoffs are likely to become complex. Also the weightage to the objectives are likely to change with respect to customer's requirement. Hence the effectiveness of fuzzy stochastic multi-objective programing [59] approaches and evolutionary multi and many-objective optimization algorithms [60] needs to be explored to address the challenges in modeling the DSM optimization problem to real scenarios.
- The choice of solution strategy or algorithm depends on many factors user load diversity, amount of user participation, tariff structure etc. there is a need for a unified and robust solution which fits to most of the problem case scenarios.
- Popularly, two level time scales are used for demand management namely a day ahead scheduling typically one hour to 12 min interval and an intraday/online optimization with time interval of few minutes as tradeoff between problem computational complexity, uncertainty considerations and useful optimal solution. Similarly, two level control optimization have been used namely individual customer level and aggregated level. Developing effective techniques for coordination between these strategies remain open.
- Implementation of effective real time renewable generation and load demand forecasting methods and challenges associated still needs to be addressed. Algorithms based on machine learning, state space models, and ANN's can be further explored [61].
- As suggested in Sect. 4 of [62], exploring and studying the applications of various game theoretic methods for multi-home level demand response management needs to be looked at.

Table 2. A summary of Key Issues along with their challenges and opportunities

Key issues	Challenges	Opportunities
Load modelling	DR enabled physical based load modeling helps to know the consumption changes with respect to customer behavior and utility signals. The key is to develop a characteristic model with following qualities comprehensive, reasonably aggregated and DR enabled as in [64].	Development of a sophisticated load model based on historical data, physical parameters, occupant comfort and DR signals at the user operation. E.g. Weather based model helps for precool and/or arrival departure preparation, reduced comfort settings of cooling load for DR response participation.
Consumer behaviour modeling	Model complexities depends on various parameters	Exploring the use of machine learning, fuzzy logic and ANFIS systems
Seamless integration of hardware & software platform	Since multiple ICTs are used at different levels of communication with mesh networking between devices and EMS for control. The issue of communication protocol for integration of HEM interoperability with smart phone, Tablets etc.,	HEMS with support of multiple communication protocols and development of standards- based open platform for easy integration.
Computational & integration challenges at individual level	A coordination is required between costumer level HEMS and community level Aggregator for DR management.	Having an integrated and hierarchical multistage optimization strategy with time receding interval.
DR integration challenges aggregated-customer level	Peak rebound occurs multiple users adopt similar algorithms for load scheduling/may not cooperate with aggregator. Uncertainty in generation, interactions of multiple renewable resources with network.	Exploring the usage of stochastic game-theoretic approaches for interactive decisions. Self-use by storing in a battery during peak times for increased system flexibility. Buy/sell to grid or supply local load.
Coordination strategies	How to obtain coordination between HEMS and Hybrid Grid connected inverter with Rooftop solar PV and battery storage. Coordination between HEMS and CEMS/Aggregator.	Development of a hybrid grid connected inverter's having programmable discharge power, time and duration for ON/OFF control by a HEMS.

(*Continued*)

Table 2. (*Continued*)

Key issues	Challenges	Opportunities
Forecasting of local RE based power generation and load demand	Near real-time generation forecast models depends on local weather profile, time interval, site specific physical shading and clouding effects etc., Load demand depends on uses occupancy, behaviour, season, time of the day etc.,	Time-series and Neural network models needs to be explored for short term generation forecasting with consideration of uncertainty in weather parameters. Demand prediction and uncertainty modeling by machine learning together with model predictive approaches
Creating Awareness	DR programs are usually voluntary, resulting in self-selection, limitation in cost effectiveness and participation	Customer education and focusing on marketing and adaptation strategies
Pricing structure	Need for profitable and attractive dynamic pricing structure	Designing a simpler pricing scheme with dynamic dependency on power and time of use
Privacy and security	User's data gives critical information about a user life style which puts a user at risk.	Data encryption, safe cloud storage systems needs to be explored to ensure privacy

- Penetration of Plugin-electric vehicles and distributed energy resources brings an increased flexibility in load shaping and integration challenges [63], effective scheduling algorithms to reduce their impact needs to be further studied.
- Dynamic modeling and scheduling of appliances power consumption, prediction of price and uncertainties in renewable energy, making DR context-aware are issues needs to be addressed by collecting a large set of time-series data.

Finally, a summary of key issues and their challenges and opportunities are presented in Table 2.

6 Conclusion

This paper presents the background of smart home energy management functions and optimal DR models for residential users. And reviewed recent methods addressing different aspects of single and multi-user residential energy management and demand response. Based on this review, it is observed that different modelling approaches are explored for household devices, uncertainty in forecasted data and user behavior, and multiple conflicting objectives. Also many scheduling optimization techniques and methodologies are proposed; however, these methods should be further studied by applying on a similar problem scenarios for appreciating their relative merits, suitability, computational complexities, and integration challenges.

Coordination of day-ahead scheduling and real-time demand response in a home needs to be focused by considering time receding optimization strategies, for integration of RE based generation and loads under the scenario of real-time pricing with effective uncertainty consideration and moderate computational complexity. Development of case specific single home and aggregated home models with common set of time-series data such as device consumption pattern, occupancy patterns, and roof-top PV/Wind generation for over a period of time for future research and analysis.

At aggregated home levels, cooperative methods will use have more impact on efficient and economic operation of micro grid/distribution network environment. The future optimization tools for residential homes must offer intelligent ways for collective management of electric loads and resources of the multiple customers with effective coordination/negotiation strategies between HEMS and CEMS/aggregator for overall optimization.

References

1. Vardakas, J.S., Zorba, N., Verikoukis, C.V.: A survey on demand response programs in smart grids: pricing methods and optimization algorithms. IEEE Commun. Surv. Tutor. **17** (1), 152–178 (2014)
2. Barbato, A., Capone, A.: Optimization models and methods for demand-side management of residential users: a survey. Energies **7**, 5787–5824 (2014)
3. Hu, Q., Member, S., Li, F., Member, S.: Hardware design of smart home energy management system with dynamic price response. IEEE Trans. Smart Grid **4**, 1878–1887 (2013)
4. RELOAD Database Documentation and Evaluation and Use in NEMS. (2001)
5. Nair, A.G., Rajasekhar, B.: Demand response algorithm incorporating electricity market prices for residential energy management. In: Proceedings of 3rd International Workshop Software Engineering Challenges Smart Grid - SE4SG 2014, pp. 9–14 (2014)
6. Shao, S., Pipattanasomporn, M., Rahman, S.: Development of physical-based demand response-enabled residential load models. IEEE Trans. Power Syst. **28**, 607–614 (2013)
7. Hopkins, M.D., Pahwa, A., Easton, T.: Intelligent dispatch for distributed renewable resources. IEEE Trans. Smart Grid **3**, 1047–1054 (2012)
8. Yu, Z., Mclaughlin, L., Jia, L., Murphy-hoye, M.C., Pratt, A., Tong, L.: Modeling and stochastic control for home energy management. Power Energy Soc. Gen. Meet. **2012**, 1–9 (2012)
9. Chen, Z., Wu, L., Fu, Y.: Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization. IEEE Trans. Smart Grid **3**, 1822–1831 (2012)
10. Fernandes, F., Sousa, T., Silva, M., Morais, H., Vale, Z., Faria, P.: Genetic algorithm methodology applied to intelligent house control. In: 2011 IEEE Symposium on Computational Intelligence Applications In Smart Grid (CIASG), pp. 1–8. IEEE (2011)
11. Sou, K.C., Weimer, J., Sandberg, H., Johansson, K.H.: Scheduling smart home appliances using mixed integer linear programming. In: IEEE Conference on Decision and Control and European Control Conference, pp. 5144–5149. IEEE (2011)

12. Tsui, K.M., Chan, S.C.: Demand response optimization for smart home scheduling under real-time pricing. IEEE Trans. Smart Grid **3**, 1812–1821 (2012)
13. Kumaraguruparan, N., Sivaramakrishnan, H., Sapatnekar, S.S.: Residential task scheduling under dynamic pricing using the multiple knapsack method. In: 2012 IEEE PES Innovative Smart Grid Technologies (ISGT), pp. 1–6. IEEE (2012)
14. Corno, F., Razzak, F.: Intelligent energy optimization for user intelligible goals in smart home environments. IEEE Trans. Smart Grid **3**, 2128–2135 (2012)
15. Ozturk, Y., Senthilkumar, D., Kumar, S., Lee, G.: An intelligent home energy management system to improve demand response. IEEE Trans. Smart Grid **4**, 694–701 (2013)
16. Mohsenian-Rad, A.-H., Leon-Garcia, A.: Optimal residential load control with rrice prediction in real-time electricity pricing environments. IEEE Trans. Smart Grid **1**, 120–133 (2010)
17. Chen, C., Wang, J., Heo, Y., Kishore, S.: MPC-based appliance scheduling for residential building energy management controller. IEEE Trans. Smart Grid **4**, 1401–1410 (2013)
18. Yoon, J.H., Baldick, R., Novoselac, A.: Dynamic demand response controller based on real-time retail price for residential buildings. IEEE Trans. Smart Grid **5**, 121–129 (2014)
19. Zuniga, K.V., Castilla, I., Aguilar, R.M.: Using fuzzy logic to model the behavior of residential electrical utility customers. Appl. Energy **115**, 384–393 (2014)
20. Edwards, R.E., New, J., Parker, L.E.: Predicting future hourly residential electrical consumption: a machine learning case study. Energy Build. **49**, 591–603 (2012)
21. Zhao, Z., Lee, W.C., Shin, Y., Song, K.: An optimal power scheduling method for demand response in home energy management system. IEEE Trans. Smart Grid **4**, 1391–1400 (2013)
22. Boynuegri, A.R., Yagcitekin, B., Baysal, M., Karakas, A., Uzunoglu, M.: Energy management algorithm for smart home with renewable energy sources. In: 4th International Conference on Power Engineering, Energy and Electrical Drives, pp. 1753–1758. IEEE (2013)
23. Hubert, T., Grijalva, S.: Modeling for residential electricity optimization in dynamic pricing environments. IEEE Trans. Smart Grid **3**, 2224–2231 (2012)
24. Ivanescu, L., Maier, M.: Real-time household load priority scheduling algorithm based on prediction of renewable source availability. IEEE Trans. Consum. Electron. **58**, 318–326 (2012)
25. Pipattanasomporn, M., Kuzlu, M., Rahman, S.: An algorithm for intelligent home energy management and demand response analysis. IEEE Trans. Smart Grid **3**, 2166–2173 (2012)
26. Kuzlu, M., Pipattanasomporn, M., Rahman, S.: Hardware demonstration of a home energy management system for demand response applications. IEEE Trans. Smart Grid **3**, 1704–1711 (2012)
27. Anvari-Moghaddam, A., Monsef, H., Rahimi-Kian, A.: Optimal smart home energy management considering energy saving and a comfortable lifestyle. IEEE Trans. Smart Grid **6**, 324–332 (2015)
28. Anvari-Moghaddam, A., Monsef, H., Rahimi-Kian, A.: Cost-effective and comfort-aware residential energy management under different pricing schemes and weather conditions. Energy Build. **86**, 782–793 (2014)
29. Jacomino, M., Le, M.H.: Robust energy planning in buildings with energy and comfort costs. 4OR **10**, 81–103 (2011)
30. Zhou, S., Wu, Z., Li, J., Zhang, X.: Real-time energy control approach for smart home energy management system. Electr. Power Compon. Syst. **42**, 315–326 (2014)
31. Mohsenian-Rad, A.-H., Wong, V.W.S., Jatskevich, J., Schober, R.: Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid. In: 2010 Innovative Smart Grid Technologies (ISGT), pp. 1–6. IEEE (2010)

32. Li, D., Jayaweera, S.K., Naseri, A.: Auctioning game based demand response scheduling in smart grid. In: 2011 IEEE Online Conference on Green Communications, pp. 58–63. IEEE (2011)
33. Zhu, Z., Tang, J., Lambotharan, S., Chin, W.H., Fan, Z.: An integer linear programming and game theory based optimization for demand-side management in smart grid. In: 2011 IEEE GLOBECOM Work. (GC Wkshps), pp. 1205–1210 (2011)
34. Zheng, D., Ge, W., Zhang, J.: Distributed opportunistic scheduling for ad hoc networks with random access: an optimal stopping approach. IEEE Trans. Inf. Theory **55**, 205–222 (2009)
35. Conejo, A.J., Morales, J.M., Baringo, L.: Real-time demand response model. IEEE Trans. Smart Grid **1**, 236–242 (2010)
36. Yi, P., Dong, X., Iwayemi, A., Zhou, C., Li, S.: Real-time opportunistic scheduling for residential demand response. IEEE Trans. Smart Grid **4**, 227–234 (2013)
37. Giannakis, G.B.: Scalable and robust demand response with mixed-integer constraints. IEEE Trans. Smart Grid **4**, 2089–2099 (2013)
38. Guo, Y., Pan, M., Fang, Y., Khargonekar, P.P.: Decentralized coordination of energy utilization for residential households in the smart grid. IEEE Trans. Smart Grid **4**, 1341–1350 (2013)
39. Samadi, P., Schober, R., Wong, V.W.S.: Optimal energy consumption scheduling using mechanism design for the future smart grid. In: 2011 IEEE International Conference Smart Grid Communication, pp. 369–374 (2011)
40. Kishore, S., Snyder, L.V.: Control mechanisms for residential electricity demand in smartgrids. In: 2010 First IEEE International Conference Smart Grid Communication, pp. 443–448 (2010)
41. Pedrasa, M.A.A., Spooner, T.D., MacGill, I.F.: Coordinated scheduling of residential distributed energy resources to optimize smart home energy services. IEEE Trans. Smart Grid **1**, 134–143 (2010)
42. Guo, Y., Pan, M., Fang, Y., Khargonekar, P.P.: Coordinated energy scheduling for residential households in the smart grid. In: 2012 IEEE Third International Conference Smart Grid Communication, pp. 121–126 (2012)
43. Safdarian, A., Member, S., Fotuhi-firuzabad, M.: A distributed algorithm for managing residential demand response in smart grids. IEEE Trans. Ind. Inform. **10**, 2385–2393 (2014)
44. Tushar, W., Chai, B., Yuen, C., Smith, D., Wood, K., Yang, Z., Poor, V.: Three-party energy management with distributed energy resources in smart grid. IEEE Trans. Ind. Electron. **62**, 2487–2498 (2014)
45. Saeedi, A.: Real time demand response using renewable resources and energy storage in smart consumers. In: 22nd International Conference on Electricity Distribution Stockholm, pp. 10–13 (2013)
46. O'Neill, D., Levorato, M., Goldsmith, A., Mitra, U.: residential demand response using reinforcement learning. In: 2010 First IEEE International Conference on Smart Grid Communications, pp. 409–414. IEEE (2010)
47. Fan, Z.: A distributed demand response algorithm and its application to PHEV charging in smart grids. IEEE Trans. Smart Grid **3**, 1280–1290 (2012)
48. Kim, B.-G., Ren, S., van der Schaar, M., Lee, J.-W.: Bidirectional energy trading for residential load scheduling and electric vehicles. In: 2013 Proceedings of IEEE INFOCOM, pp. 595–599 (2013)
49. Wijaya, T.K., Banerjee, D., Ganu, T., Chakraborty, D., Battacharya, S., Papaioannou, T., Seetharam, D.P., Aberer, K.: DRSim: a cyber physical simulator for demand response systems. In: 2013 IEEE International Conference on Smart Grid Communications, SmartGridComm 2013, pp. 217–222 (2013)

50. Morais, H., Kádár, P., Faria, P., Vale, Z.A., Khodr, H.M.: Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. Renew. Energy **35**, 151–156 (2010)
51. Thevampalayam, A., Sathiakumar, S.: Peak demand management in a smart community using coordination algorithms. Int. J. Smart Home **7**, 371–390 (2013)
52. Aghaei, J., Alizadeh, M.-I.: Demand response in smart electricity grids equipped with renewable energy sources: a review. Renew. Sustain. Energy Rev. **18**, 64–72 (2013)
53. Barbato, A., Carpentieri, G.: Model and algorithms for the real time management of residential electricity demand. In: 2012 IEEE International Energy Conference and Exhibition (ENERGYCON), pp. 701–706. IEEE (2012)
54. Faria, P., Soares, J., Vale, Z., Morais, H., Sousa, T.: Modified particle swarm optimization applied to integrated demand response and DG resources scheduling. In: 2014 IEEE PES T&D Conference Exposition, p. 1 (2014)
55. Bellifemine, F., Caire, G., Greenwood, D.: Developing Multi-Agent Systems with JADE. John Wiley & Sons Ltd, Chichester (2007)
56. GridLab-D software. http://www.gridlabd.org/
57. Asare-Bediako, B., Kling, W.L., Ribeiro, P.F.: Integrated agent-based home energy management system for smart grids applications. IEEE PES ISGT Eur. **2013**, 1–5 (2013)
58. Khan, A.A., Razzaq, S., Khan, A., Khursheed, F.: HEMSs and enabled demand response in electricity market: an overview. Renew. Sustain. Energy Rev. **42**, 773–785 (2015)
59. Zhang, X., Huang, G.H., Chan, C.W., Liu, Z., Lin, Q.: A fuzzy-robust stochastic multiobjective programming approach for petroleum waste management planning. Appl. Math. Model. **34**, 2778–2788 (2010)
60. Deb, K., Jain, H.: An evolutionary many-objective optimization algorithm using reference-point based non-dominated sorting approach, part I: solving problems with box constraints. IEEExplore IEEE Org. **18**, 577–601 (2013)
61. Spiess, J., Joens, Y.T., Dragnea, R., Spencer, P.: using big data to improve customer experience and business performance. Bell Labs Tech. J. **18**, 3–17 (2014)
62. Saad, W., Han, Z., Poor, H.V., Başar, T.: Game theoretic methods for the smart grid. IEEE Signal Process. Mag. Spec. Issue Signal Process. Tech., Smart Grid (2012)
63. Zhao, J., Kucuksari, S., Mazhari, E., Son, Y.-J.: Integrated analysis of high-penetration PV and PHEV with energy storage and demand response. Appl. Energy **112**, 35–51 (2013)
64. Shao, S., Pipattanasomporn, M., Rahman, S.: Development of physical–based demand response–enabled residential load models. IEEE Trans. Power Syst. 28, 607—614 (2013)