Advances in Building Energy Research

ISSN: 1751-2549 (Print) 1756-2201 (Online) Journal homepage: www.tandfonline.com/journals/taer20

Smart home energy management system – a review

Altaf Q. H. Badar & Amjad Anvari-Moghaddam

ADVANCES IN BUILDING ENERGY RESEARCH
2022, VOL. 16, NO. 1, 118–143
https://doi.org/10.1080/17512549.2020.1806925

Taylor & Francis
Taylor & Francis Group

Check for updates

Smart home energy management system – a review

Altaf Q. H. Badar [a] and Amjad Anvari-Moghaddam [b,c]

[a]Electrical Engineering Department, National Institute of Technology, Warangal, India; [b]Department of Energy Technology, Aalborg University, Aalborg East, Denmark; [c]Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran

ABSTRACT
Smart grid is providing new opportunities and techniques for supplying high energy demand of the ever growing energy industry. One-third of the total energy demand comes from the residential sector. A new frontier in this field is the Energy Management Systems being designed for the futuristic smart homes. A smart home is a home that shall be able to decide, control and optimize the operation of its equipments, on its own with minimal interference from its master, a human. One of the major factors for the successful development of a smart home is its ability to manage the energy resources including generation and storage. The recent smart home energy management publications have been reviewed in detail in this paper. The paper also elaborates on different demand response strategies used and the various equipments considered along with renewable energy generation and plug in electric vehicles (EV) employed in smart home energy management process. The literature is categorized based on various factors like tariff, storage, trading, monitoring, etc. affecting the performance of a smart home. These factors are mentioned, discussed and analysed in depth. Objective functions, constraints and communication models involved in smart home energy management models are also surveyed.

ARTICLE HISTORY
Received 9 November 2019
Accepted 1 August 2020

KEYWORDS
Smart home energy management systems; appliance scheduling; demand response techniques; smart home architecture; renewable energy source

1. Introduction

The twenty-first century is marked with unprecedented growth in human inventions and standard of living. The improvement in the standard of living results in high consumption of electricity thus leading to high energy demand from the utilities. The per capita energy consumption in Norway and the USA is approximately 2.6 and 1.4 kW compared to 5–11 watts in some African countries (Energy Consumption By Country 2020, 2020). On development of these underdeveloped countries, more energy will be demanded certainly.

The residential consumption lies in the range of around 13–37% (CEA, 2020) of the total load. The implementation of demand response techniques will help reduce the consumption of electricity and provide other benefits like providing high utility factors for generation plants, improved reliability, balanced peak and base loads, etc.

The residential load is made of homes. The users of these homes have a preference (pattern) for power consumption (Chen et al., 2017; Jin et al., 2017). This preference

CONTACT Altaf Q. H. Badar altafbadar@nitw.ac.in, altafbadar@gmail.com

usually depends on factors like temperature, humidity, holiday, etc. (Chawda et al., 2017; Chen et al., 2017). Based on the analysis of these factors, the consumption of a particular home can be forecasted. This load forecasting can be used to suit the scheduling of appliances and implementation of demand response techniques. Hence, forecasting can also play a very important factor in the optimal working of SHEMS.

The homes consist of two types of loads, viz. controllable and uncontrollable (Basit et al., 2017; Yao et al., 2017; Zunnurain & Maruf, 2017). The controllable loads are those whose demand over the time can be managed whereas for uncontrollable loads the timings cannot be controlled. For example, in washing machine the timings of its operation can be managed whereas lighting load cannot be delayed. The controllable loads are the ones which shall be used for appliance scheduling in an SHEMS and which will implement the demand response techniques. The uncontrollable loads are a part of the total load of a home but their working cannot be scheduled.

The reduction of cost of renewable energy sources has opened new opportunity for the consumers to produce their own electricity. This means that while considering a smart home, the renewable energy sources will also have to be included. The renewable energy sources bring with them calculations related to their generation forecasting, storage strategies, etc.

Other than these considerations, a smart home energy management system could also consist of battery/storage management, Electric Vehicle (EV) charging along with Vehicle to Grid (V2G), forecasting, appliance scheduling, etc.

The review paper aims to present different objectives, constraints, models, etc. from a wide variety of literature on SHEMS. These research work/publications have discussed and proposed solutions for different factors which affect the optimal operation of SHEMS. These factors are mentioned, discussed, classified and analysed in depth in this paper, thus bringing forth the shortcomings or research areas which require more consideration. Tables and graphs are used for better representation purposes.

Some of the factors affecting the performance of SHEMS are: tariff, interaction of multiple SHEMS for creating a neighbourhood energy management system, distributed generation, etc. This paper is organized as follows: Section II presents an insight into SHEMS, Section III deals with SHEMS Architecture, Section IV presents SHEMS Modelling and Formulation which encompasses different mathematical equations related to SHEMS, Section V discusses different Optimization Techniques and Solution Methods, Section VI presents SHEMS Communication models of different research papers, Section VII discusses the Forecasting of residential load for an SHEMS, Section VIII introduces Energy Trading and Tariff for SHEMS environment and Section IX presents a summary through Conclusion.

2. Smart Home Energy Management System

Smart Home Energy Management System (SHEMS) requires the development of a framework to handle the energy needs, demands and resources of a home to reduce the energy costs without compromising the comfort levels of the user. The framework should be developed in such a way to take decisions on its own without much involvement of the user.

To optimize the system, initially the problem is formulated. This exercise gives information about the parameters being input to the system and their relationship with the output. The output is usually the energy costs. Various input parameters can be tariff rates, load forecasting, appliances and their level of importance, etc.

Optimization is required after the problem has been formulated. Various mathematical based and meta-heuristic techniques can be applied for this purpose. The selection of optimization technique shall be dependent on the examined problem and its ability to meet certain objectives such as reducing energy bill, maximizing User Comfort (UC), reducing load during peak hours, reducing peak to average ratio and optimizing appliance operating time.

SHEMS framework shall normally be based on the following process: data collection and monitoring, data processing and analysing, forecasting/estimation (if needed), optimization and execution. Other than these processes, some communications are also required between the SHEMS framework and the grid or other third parties for related data exchange (such as energy tariffs, base load determination, etc.) at a future time. SHEMS needs to also communicate for controlling the working of appliances, storage system and generation from renewable energy sources (RES).

Monitoring the energy usage of a home is of prime importance. It helps in understanding the pattern of energy consumption in a home. This can be used for forecasting energy usage at a later date and thus utilizing demand response (DR) techniques to optimize energy consumption. There are two major approaches of load monitoring: Intrusive Load Monitoring and Non Intrusive Load Monitoring (Abubakar et al., 2017; Zhai et al., 2018). Intrusive Load Monitoring is when the load consumption of a home is monitored directly by observing the ON/OFF conditions of the appliance as is done in Zhai et al. (2018) with the help of smart plugs. Non Intrusive Load Monitoring deals with different methods of estimating the appliances that are consuming a certain amount of load at a given time in a home. These are indirect methods of monitoring the load consumption pattern. Intrusive Load Monitoring is based on distributive sensing while Non Intrusive Load Monitoring is single point sensing (Abubakar et al., 2017). Techniques related to these methods are surveyed in Faustine et al. (2017) for Non Intrusive Load Monitoring and Ridi et al. (2014) for Intrusive Load Monitoring.

Analysis of stored data along with its application to attain the objective of SHEMS is reached through different algorithms. Forecasting of different parameters plays a very important role in the implementation of SHEMS. Forecasting might be required for different purposes such as load consumption or RES determination.

Another important factor affecting the performance of SHEMS is the inclusion of storage systems. Storage systems help in easily rescheduling the usage of various home appliances. It provides reliability in energy supply. Storage systems can also play an important role in bringing down energy bills. Different energy storage systems considered are: batteries, thermal energy storage and EVs.

3. SHEMS architecture

In Zhai et al. (2018), a very simple architecture of a smart home is presented as shown in Figure 1. The SHEMS unit is connected to each and every equipment through a smart plug. The smart plug can be used to monitor and control the usage of the equipment. The SHEMS unit also communicates with the gateway to receive the DR commands from the utility. The RESs are not considered in this architecture.

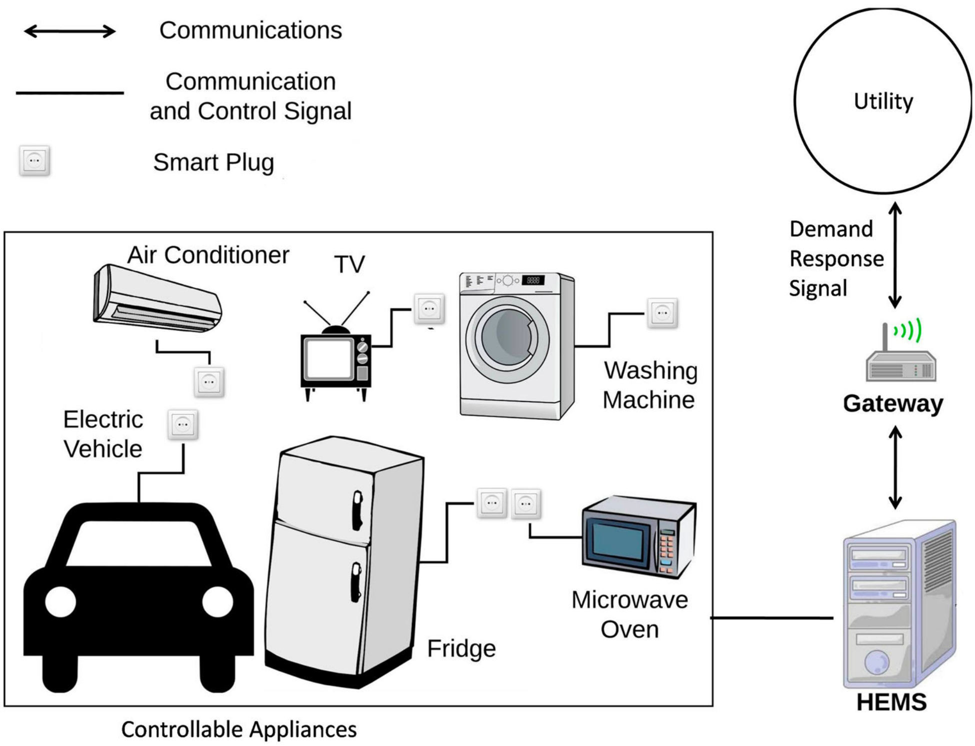

Figure 1. Architecture of SHEMS in Zhai et al. (2018).

The structure presented by Pawar and Vittal (2017) as shown in Figure 2 is quite similar to the one presented in Zhai et al. (2018), except that in Pawar and Vittal (2017), the RES and storage systems are also shown as a part of SHEMS. The structure used by Killian et al. (2018) as shown in Figure 3 further adds capacitors into the SHEMS environment. Figure 3 shows the possible flow of electric power.

The model predictive control (MPC) proposed in Jin et al. (2017) is placed in the centre as shown in Figure 4. This MPC is supposed to interact with utility as well as different equipments in the smart home. Each equipment in the home has its own controller or meter and can interact with the MPC. The examined system also includes a PhotoVoltaic (PV) array and a battery system. Another block is placed to represent the measurement and learning process of the system based on the history of energy usage. This block also helps identify various patterns in which the appliances were used. The system identification block is used to sense the current usage pattern in the home. These patterns will depend on various factors like weather, etc. The MPC is also responsible to gather data related to weather and user's preferences. There is an interface with utility for forecasting of load and to receive information related to any DR events initiated by the utility. The MPC shall be required to implement any DR event.

The architecture of a smart home detailed in Zunnurain and Maruf (2017) and shown in Figure 5 represents an SHEMS system which is connected to the utility through a smart meter. The smart home itself does not have any RES, however, it employs a storage system. The appliances in the smart home are clearly classified into critical and non-critical

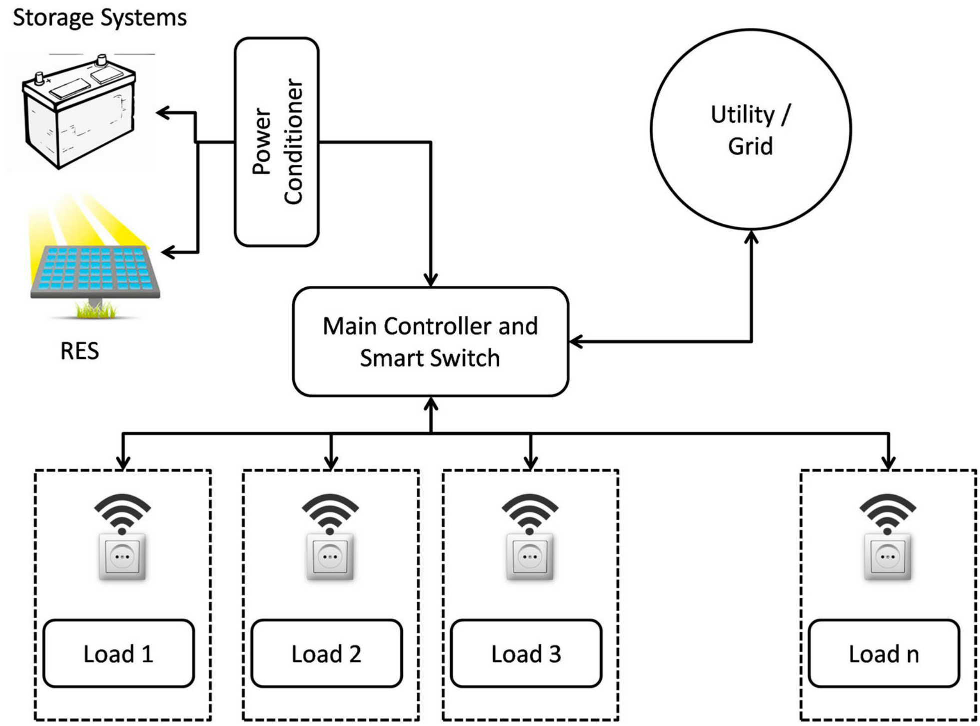

Figure 2. Structure of SHEMS in Pawar and Vittal (2017).

loads. Priority allotment to an appliance shall depend on this classification. The SHEMS utilizes load shifting technique algorithm which is embedded onto the centralized HEMS controller. User preferences are, however, not considered in this model.

The SHEMS as part of a whole grid is shown in Figure 6. Authors in Yener et al. (2017) present a whole grid system which has smart homes as a part of it. The main grid centre is connected to its own database and control server along with client home server. The client home server in turn is connected to RES and loads within the smart home. The client home server is controlled by the client through a mobile device. The methodology implemented

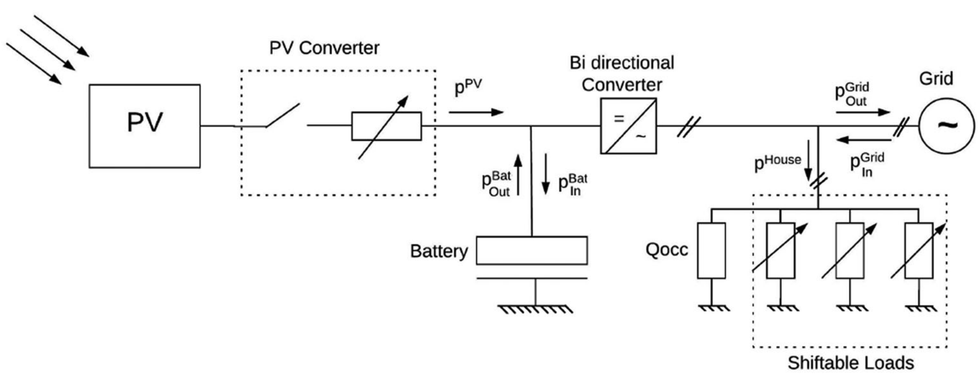

Figure 3. Structure of SHEMS in Killian et al. (2018).

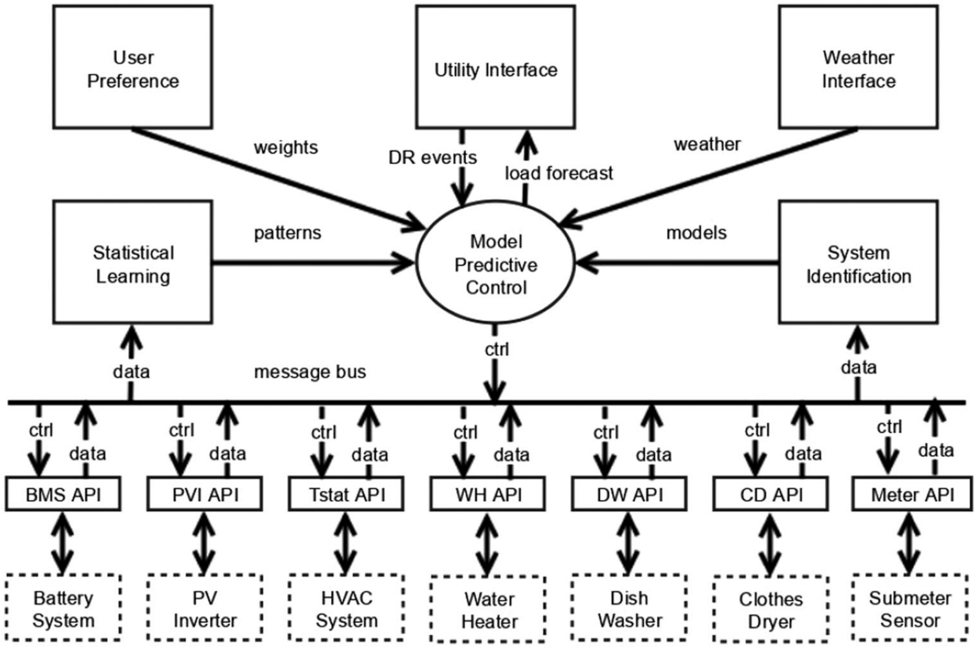

Figure 4. Structure of SHEMS in Jin et al. (2017).

aims to gather information related to DR events for end users and system operators. It also allows the end user to monitor the implementation of the DR event. The main server is connected to the control centre and the database. This main server is required to interact with the client server for controlling of appliances and implementation of the DR events. The client/user groups are connected with the main server as well as the client server. The model assumes the presence of RES in the system.

A comprehensive SHEMS is presented in Luo et al. (2019). Figure 7 presents the proposed architecture. The SHEMS takes into consideration a wide variety of inputs for an optimal management of energy usage. The dashed line represents the controlling action of SHEMS. The inputs to the SHEMS consist of

- Natural Aggregation Algorithm: It is used to search for an optimal solution in the provided search space.
- Solar database: The solar database provides for the forecasted solar power generation. It takes into consideration the current weather conditions and the historical data from its database to forecast the power that shall be generated from the PV panels.
- Home Database: The home database is used to suggest the historical usage of uncontrollable load of the home and the peak power usage of the home. This data is useful in scheduling of the controllable load of the home.
- Constraints: There are various operational constraints in an SHEMS which are taken care of by this input. The appliance dependent constraints are also considered in the proposed structure.
- Tariff: The real-time pricing and the other charges are input to the SHEMS. The tariff is responsible for real-time pricing and demand charge tariff-related information.

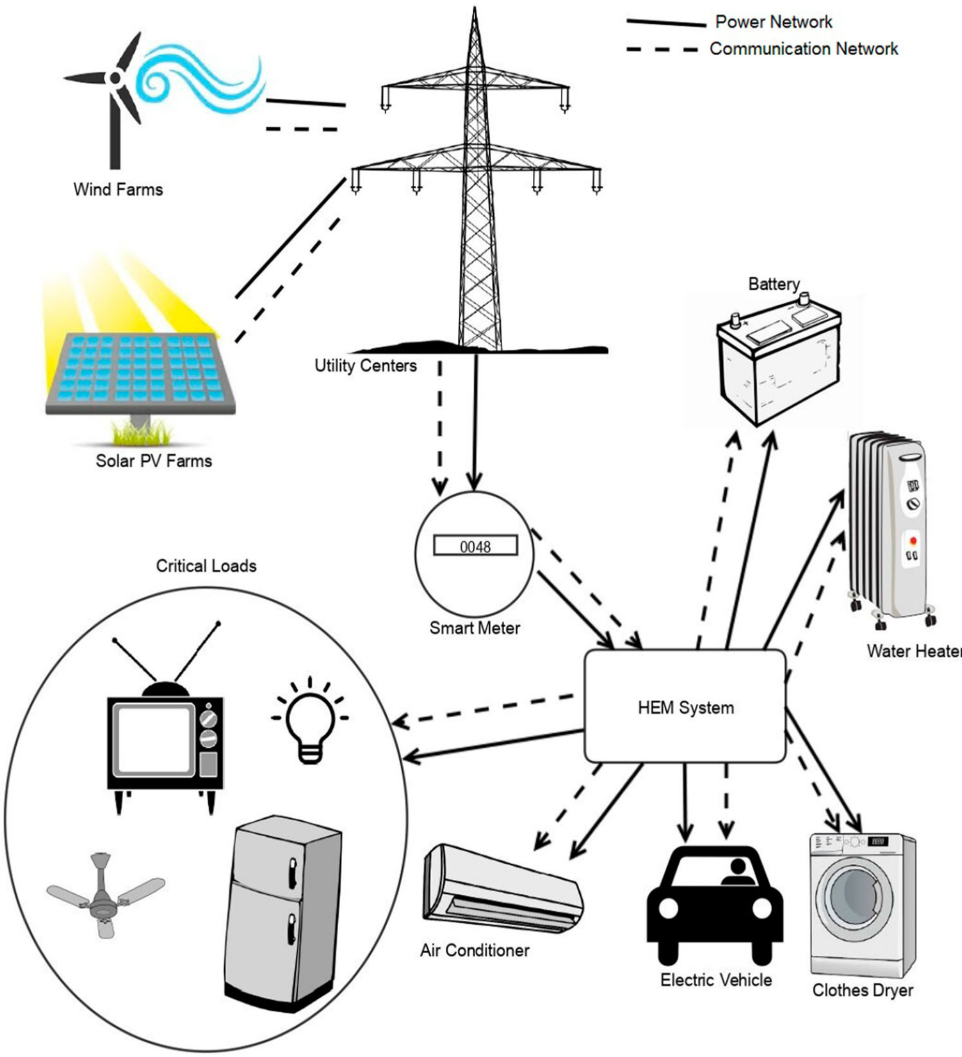

Figure 5. Architecture of SHEMS in Zunnurain and Maruf (2017).

- Controllable Appliance Models: The data related to the controllable appliances in the home is also provided to the SHEMS. It is a two-way communication with this input as the controllable appliances are also required to be scheduled for realizing optimal operating costs.
- Energy Storage: The energy storage is another input in the SHEMS which has a two-way communication with the SHEMS. The Energy storage model shall provide details related to the available energy storage facilities in the home while the SHEMS controls the charging/discharging of the Battery Energy Storage System (BESS).

Another SHEMS architecture with a difference is presented in Lokeshgupta and Sivasubramani (2019). The architecture also introduces a dump load in combination with RES as shown in Figure 8. Dump load is introduced for the wind power in the system.

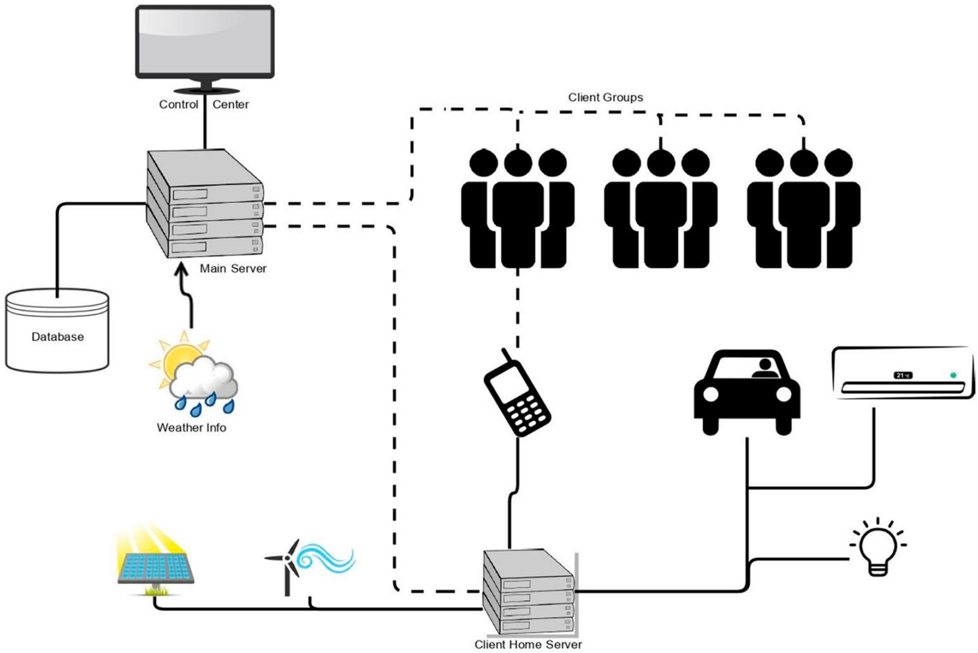

Figure 6. Structure of SHEMS as part of grid in Yener et al. (2017).

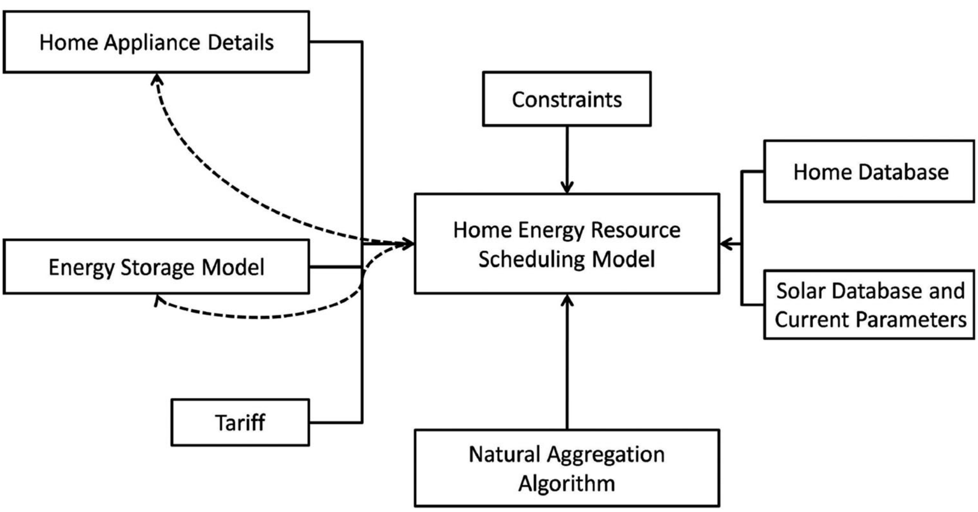

Figure 7. Structure of SHEMS in Luo et al. (2019).

4. SHEMS modelling and formulation

The problem statement of SHEMS depends on various constraints and objectives based on factors being considered. In this section, a number of objectives and constraints from various research papers are presented. The objective function for a smart home energy

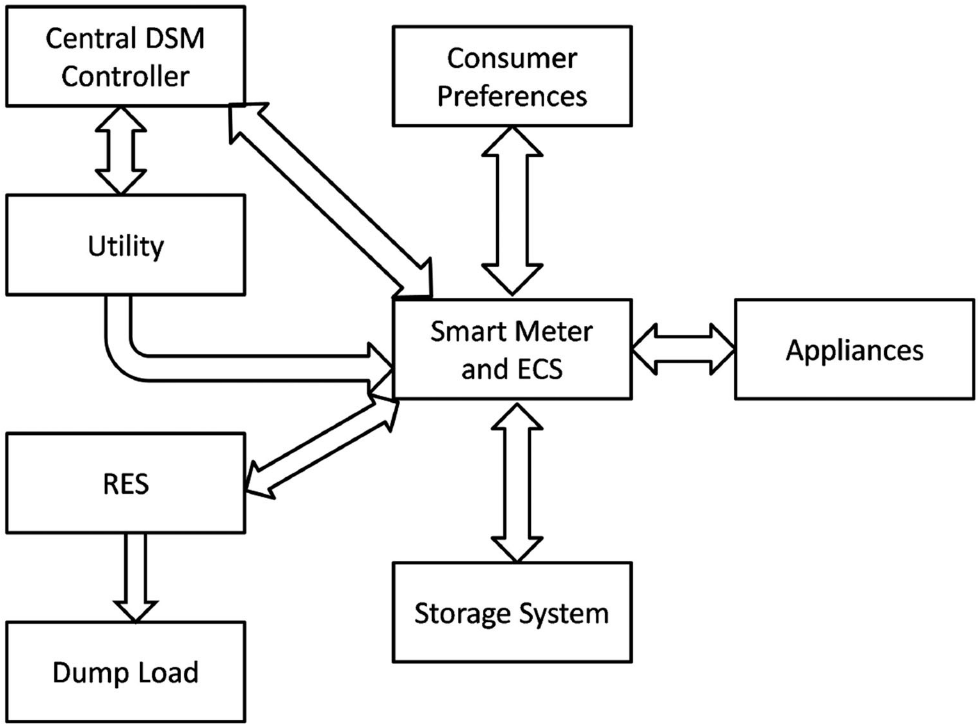

Figure 8. Structure of SHEMS in Lokeshgupta and Sivasubramani (2019).

management system in Celik et al. (2017a) is given as

$$\min\,(C_u) = \sum_{t=1}^{\tau} (P_u^n(t) - P_u^s(t)) \cdot \lambda(t, P_n(t)) \tag{1}$$

The above equation (1) signifies the minimization of the user's utility bill defined as the product of the difference between the load profile of the home and energy sold by a smart home and the energy price. The terms used in the equation are: C_u is the daily electricity bill, τ is the maximum value in the time set, $P_u^n(t)$ is the home net power profile at time interval 't', $P_u^s(t)$ is the power sole through the discharge of the battery at time interval 't' and $\lambda(t, P_n(t))$ is the electricity price scheme. Equation (1) is also used for the optimization of SHEMS in Celik et al. (2017b).

Authors in Killian et al. (2018) present a complex objective function for a smart home having thermal synchronization as

$$\begin{aligned} \min\,(J_u) = \sum_{k=0}^{n_p} [(&\vartheta_k^{\text{ref}} - \vartheta_k^{\text{act}})' \mathcal{Q}_k (\vartheta_k^{\text{ref}} - \vartheta_k^{\text{act}}) \\ &+ \triangle u_k' \mathcal{R}_k \triangle u_k + (g_k^{\text{buy}} \mathcal{S}_k + \mathcal{P}_k) p_{\text{in},k}^{\text{grid}} - g_k^{\text{sell}} \mathcal{S}_k p_{\text{out},k}^{\text{grid}}] \end{aligned} \tag{2}$$

Equation (2), takes care of user's comfort (Q_k), manipulated variables (R_k), cost of per unit of energy bought from the grid (S_k), maximizing cost of energy produced by RES (P_k), flexible price for buying and selling (g) and power taken and supplied to the grid (p), over the given period of time given by n_p. Equation (2) presents a more elaborated objective function while considering for UC, and separating the factors involved as compared to the earlier equation.

The cost of electricity consumption is optimized in Jeddi et al. (2017). The equation is simple in its construct and only deals with the cash received and paid along with battery-related costs. It does not consider UC as a part of the equation. The equation used is

$$\text{CoEC} = \sum_{t=1}^{T} [\text{CP}(t) + \text{CR}(t) + C_{\text{BD}}(P_{\text{BESS}}(t))] \tag{3}$$

In the above equation, CP signifies cash paid while cash received is given by CR. C_{BD} signifies the cost of BESS degradation and P_{BESS} gives the power of BESS.

A detailed modelling of battery and its inclusion in the main objective function for reducing overall electricity cost is presented in Wei et al. (2017) as

$$\begin{aligned}\sum_{k=0}^{\infty} \gamma^k (m_1 (C_k P_{\text{G},k})^2 + m_2 \left(E_{\text{B},k} - \frac{1}{2}(E_b^{\min} + E_b^{\max}) \right)^2 \\ + m_3 (P_{\text{BL},k} - (P_{\text{RB},k} + P_{\text{GB},k}))^2)\end{aligned} \tag{4}$$

γ is the discount factor in the above equation, whereas m_1, m_2 and m_3 are positive constants. C_k provides for the electricity rate for each unit, $P_{\text{G},k}$ is the power supplied by the grid, $P_{\text{BL},k}$ is the power supplied by the battery to the load, $P_{\text{GB},k}$ is the power supplied to the battery by the grid and $P_{\text{RB},k}$ is the power supplied by the RES to the battery. For battery energy $E_{\text{B},k}$ is used, whereas $E_b^{\min}$ and $E_b^{\max}$ represent the minimum and maximum energy storage in the battery. The equation considers various factors which contribute to the costs and earnings in an SHEMS. A number of factors are introduced in the equation, whose values will play a major part in the evaluation of the objective function. These factors shall also be helpful to distinguish various conditions affecting SHEMSs.

Some of the other important components of an SHEMS are the heating, ventilation and air conditioning (HVAC) load. These components are considered in Y. Liu et al. (2017) and given in the equation as

$$J = \min \left(\sum_{k=1}^{K} D(k) P^{\text{SH}}(k) \triangle(t) + \sum_{k=1}^{K} \sum_{i=1}^{M} \omega_i s_i |T_i^{\text{in}}(k+1) - T_i^d(k+1)| \right) \tag{5}$$

Equation (5) is a single time scale optimization of SHEMS, where all terms are related to fast time scale. $D(k)$ represents dynamic price and P^{SH} gives the power consumption over a time interval $\triangle t$. Discomfort level of the user is given by ω_i, s gives the switch position of HVAC, T^{in} is for indoor temperature and T^d gives the desired temperature. Equation (5) introduces terms related to temperature and relates the UC through it, while considering dynamic pricing of electricity. The RES as well as BESS are not a part of the equation. In Y. Liu et al. (2017), multi-time scale optimization is presented. The time period of optimization for an SHEMS is first divided into slow time scale. Now each interval in slow time scale is considered as a period and is further distributed into fast time scale.

EVs will also be forming an important part of SHEMS, whose modelling is accomplished with the help of Markov chain model in Wu et al. (2016). The equation for optimization is formulated as

$$P_{\mathrm{grid},k} = S_k P_{\mathrm{evc},k} + P_{\mathrm{dem},k} - P_{\mathrm{pv},k} \tag{6}$$

The electric power from the grid (P_{grid}), power demand of the home (P_{dem}), Plug in Electric Vehicle (PEV) battery charger power (P_{evc}) and power supplied from the PV array (P_{pv}) form the part of the equation. The state of PEV is given by S. Equation (6) is a very simplistic representation of an objective function for an SHEMS involving PEV. However, the equation misses out on BESS as a separate entity in the SHEMS as well as there is no representation for UC level.

A variety of appliances are considered in Yao et al. (2017), where some of the appliances can be controlled. The objective function also considers reducing the waiting time for the operation of the appliance. The appliances are marked to signify whether they can be controlled or not. The objective function is subjected to different constraints and is expressed as

$$\min \sum_{j=k}^{N} \frac{\rho^j \omega_a^j P_a^j}{\Delta T} \tag{7}$$

In above equation, 'ρ' represents electricity price, 'ω' represents cost of waiting time, 'P' represents power consumed by an appliance, 'a' represents individual appliances being considered in the smart home and 'ΔT' represents available slot in each hour. Also 'j' gives the time step whereas 'k' represents current time step. The objective function in Yao et al. (2017) is totally dedicated to reducing appliance waiting time. In many of the references, appliance waiting time is directly related to UC, and thus we can state that the primary objective in this case is only UC. The RES, BESS and PEV are not a part of the objective function.

Foresee is a user-centric SHEMS presented in Jin et al. (2017). The SHEMS is supposed to cater a multi-objective model along with predictive control framework. The concerns in the research are user needs, energy efficiency, reliability and energy costs. The minimization of objective function is given as

$$J(x_0, U) = \min \sum_{t=0}^{H-1} B\Phi^T(x(t), U(t)) \tag{8}$$

In the above equation, 'J' presents a linear combination of multiple objectives for the horizon used in prediction. 'H' is the horizon for prediction. The objective function is the combination of initial equipment status 'x_0' and control actions 'U'. 'B' represents a set of weighting factors for user preferences required for individual objectives. 'Φ' is a row matrix representing the functions used for obtaining the cost of individual objectives. A set of time-dependent variables representing the equipment status is given by '$x(t)$' and control actions by '$U(t)$'. The paper considers various factors like thermal discomfort, energy cost, carbon emission, user inconvenience and equipment degradation. Constraints considered in this study are: battery, HVAC, water heater, schedulable appliance, PV and power balance. The equation is a combination of multiple actions, however, the RES and PEV do not appear to be a part of the objective function.

The impact of data quality on SHEMS is studied in Kang et al. (2018). The objective function presented in this study is

$$\min_{P^{\text{net}},\delta} J = \sum_{u\in U}\sum_{t\in T}\pi_t P^{\text{net}}_{u,t} + \sum_{u\in U}\in_u \sum_{t\in T}\delta_{u,t} \tag{9}$$

In the above equation, the first term gives the daily electricity cost where 'π_t' is the electricity price and '$P^{\text{net}}_{u,t}$' is the net consumption. The second term gives the amount of user discomfort where '$\in$' gives the penalty parameter and '$\delta_{u,t}$' is a relaxation variable that gives the deviation in temperature. The equation is very simplistic yet accommodative in its presentation. The first part of the equation can be used to inculcate all kinds of costs including RES and PEV as well as different tariff structures.

In Lokeshgupta and Sivasubramani (2019), SHEMS is modelled as a multiobjective problem. Cooperative game theory is used to get the optimal operating conditions. The SHEMS consists of two objective functions given by Equation (10).

$$\min F_1 = \sum_{t=1}^{T} P^t_{\text{grid}} \cdot \tau \cdot \rho(t) \tag{10a}$$

$$\min F_2 = \text{EPL} \tag{10b}$$

F_1 is used to reduce the energy bill of the consumer and F_2 is for optimizing Electric Peak Load (EPL) demand. In the first subequation, P^t_{grid} is power consumed from the grid at a given time, τ is the time slot which is of 0.5 h and $\rho(t)$ is the electricity price per unit at a given time 't'. In the second subequation, EPL is to be minimized with a condition that it should be less than the total load demand of the home.

The most common constraints considered over a number of research papers for SHEMS are enlisted below along with some selected ones.

In Celik et al. (2017a), an equation for finding load profile of a smart home is presented as given below:

$$P^c_u(t) = \sum_{l=1}^{\mathcal{L}u} P^l_u(t) \quad \forall t \in T \tag{11}$$

In the above equation, the smart home load profile is equated to the sum of load profiles of individual appliances. This equation is also considered as an equality constraint in some papers. Similar equations appear in Killian et al. (2018), Celik et al. (2017b), Yassein (2018) and Lorestani et al. (2017).

Another equality constraint is presented in Dong and Chen (2018), showing the balance of power in an SHEMS:

$$P_{\text{G}} + P_{\text{RE}} = P_{\text{L}} + P_{\text{BT}} \tag{12}$$

The power entering the SHEMS is given by P_{G} from the grid and P_{RE} from the RESs. The load in the SHEMS is given by P_{L} for the load and P_{BT} for the battery.

The other most commonly used constraint for battery charging as well as discharging in an SHEMS framework is

$$\text{SOC}_{\min} \leq \text{SOC}(t) \leq \text{SOC}_{\max} \tag{13}$$

The state of charging (SOC) of battery at a given time is given by SOC(t), whereas SOC_{min} and SOC_{max} give the minimum and maximum SOC of the battery. The above equation can also be used for batteries within EVs, however, timing constraint needs to be introduced. The above equation is utilized by Killian et al. (2018), Jin et al. (2017), Celik et al. (2017a, 2017b), Jeddi et al. (2017), Kang et al. (2018), Lorestani et al. (2017), Dong and Chen (2018), Lokeshgupta and Sivasubramani (2019) and Monyei et al. (2018).

Some of the other constraints presented by various authors are as follows. In Killian et al. (2018), a constraint is introduced for charging and discharging rate of batteries as

$$P^{\mathrm{bat}}_{\mathrm{out},k} - \delta^{\mathrm{bat}}_{k} P^{\mathrm{bat,dis}}_{\mathrm{max}} \leq 0 \tag{14a}$$

$$P^{\mathrm{bat}}_{\mathrm{in},k} - (1 - \delta^{\mathrm{bat}}_{k}) P^{\mathrm{bat,ch}}_{\mathrm{max}} \leq 0 \tag{14b}$$

In the above equations, $P^{\mathrm{bat}}_{\mathrm{out},k}$ and $P^{\mathrm{bat}}_{\mathrm{in},k}$ give the power going out and coming in the battery, respectively. A binary variable $\delta^{\mathrm{bat}}_{k}$ is used to signify whether charging or discharging of a battery is possible. The maximum discharging rate and charging rate of the battery is given by $P^{\mathrm{bat,dis}}_{\mathrm{max}}$ and $P^{\mathrm{bat,ch}}_{\mathrm{max}}$, respectively.

In Jin et al. (2017), another constraint for batteries is included as presented below:

$$0 \leq U^{\mathrm{ch}}_{\mathrm{bat}}(t), \quad U^{\mathrm{dis}}_{\mathrm{bat}}(t) \leq 1 \tag{15}$$

This constraint defines the range of normalized battery control variables. A similar constraint is also introduced for HVAC control variables. This paper also introduces a constraint for curtailment of power from PV as

$$0 \leq U_{\mathrm{pv}} \leq 1 \tag{16}$$

The power curtailment from PV panels is given by a continuous variable U_{pv} which is bounded between 0 and 1, representing no and full curtailment, respectively. Scheduling of appliances is also subjected to a similar constraint. The author introduces another constraint to make sure that the battery power is consumed within the meter as

$$U^{\mathrm{ch}}_{\mathrm{bat}}(t) P^{\mathrm{ch,max}}_{\mathrm{bat}} - U^{\mathrm{dis}}_{\mathrm{bat}}(t) P^{\mathrm{dis,max}}_{\mathrm{bat}} + P_{\mathrm{load}}(t) \geq 0 \tag{17}$$

In the above equation, 'U' represents control variable and 'P' represents power, 'ch' is used for charging and 'dis' is for discharging, while 'bat' represents battery.

A very simple constraint/equation that should be a part of SHEMS by default is that the energy in BESS at the end of the time period should be the energy of BESS at the beginning of the next time period. In Hemmati (2017), this relation is mentioned as

$$E^{0}_{\mathrm{BESS}} = E^{T+1}_{\mathrm{BESS}} \tag{18}$$

Many more constraints are presented in a variety of ways in different research papers, however due to space constraints, the listing has been restricted to above-mentioned equations.

5. Optimization techniques and solution methods

Home agents are used for optimizing the implementation of the SHEMS in Celik et al. (2017a). For shiftable appliances, a scheduling interval is defined by the user and appliance operation is optimized by the home agent. The home agent is also responsible for charging/discharging of storage systems as well as EVs.

Home agents are used in Celik et al. (2017b) to optimize a decentralized SHEMS problem. The home agents try to optimize the social benefits through scheduling of appliances and controlling the use of energy storage systems. The energy of a smart home is shared within the neighbourhood. One of the objectives of the home agents is also to reduce the aggregated peak load in the neighbourhood. The home agents solve the problem through the use of genetic algorithm.

An MPC-based scheme is designed as mixed integer quadratic programming (MIQP) in Killian et al. (2018). The input values to MIQP-MPC are weather forecast, occupancy prediction, reference temperature set by user, weights defined by user, prices and constraints of smart grid. The weights chosen by the user signify a trade-off between comfort, cost and energy efficiency. The variables generated using MIQP – MPC are input to the electric plant and thermal pump. These variables are classified as continuous, semi continuous and discrete.

Dynamic programming breaks down large problem into several simpler subproblems in a recursive manner such that optimal solutions of these subproblems can be calculated in steps. The advantage of dynamic programming is that it can be used to solve linear, non-linear, convex or non-convex problems. In Jeddi et al. (2017), state variables are used to represent a given state, which are optimized through dynamic programming. The algorithm ends when the initial state is reached. Dynamic Programming technique is also used by Wei et al. (2017).

In optimizing SHEMS in Dong and Chen (2018), it is assumed that the surplus power is known in advance. The optimization process is classified into offline and online. In offline optimization, the objective function is known whereas in online optimization the objective function is not known. To handle time varying terms in the objective function, a time varying coefficient is introduced. Three problem functions are formulated to handle different situations. Single grid connected home microgrid optimization is proposed in Dong and Chen (2018) through Bayesian Optimization Algorithm.

Dijkstra Algorithm is used for SHEMS optimization in Basit et al. (2017). Another sub-optimal algorithm is also proposed. It attempts to optimize hourly performance by controlling schedulable and real-time appliances, while keeping total demand under limits.

In Yao et al. (2017), authors utilize Mixed Integer Linear Programming (MILP) for solving the problem of SHEMS. The objective is to reduce the electricity cost and waiting time for schedulable appliances while prioritizing power consumption from RESs. This optimization is achieved while classifying appliances into interruptible, uninterruptible and variable loads. MILP is also used in a number of research papers like Melhem et al. (2017), Marzband et al. (2017), Hao et al. (2017), Nizami and Hossain (2017), however, due to the lack of availability of space they are not discussed individually.

Heuristic optimization techniques like Harmony Search Algorithm (HSA), Bacterial Foraging Optimization (BFO) and Enhanced Differential Evolution(EDE) are utilized for SHEMS optimization in Zafar et al. (2017), whereas Javaid et al. (2017) apply BFO, Genetic Algorithm (GA), Binary Particle Swarm Optimization (BPSO), Wind Driven Optimization (WDO) and Genetic BPSO (GBPSO). Similar techniques are presented along with a hybrid technique in Ahmad et al. (2017).

Table 1. Comparative performance of optimization techniques for various SHEMS factors from Zafar et al. (2017).

Energy consumption (kWh)	Peak to Avg ratio	User comfort (UC)
HSA	EDE	BFA
EDE	BFA	EDE
BFA	HSA	HSA

Table 2. Optimization methods applied for SHEMS.

S. No.	Optimization technique	References
1	Multi Agent/Home Agents	Celik et al. (2017a, 2017b)
2	Dynamic Programming	Jeddi et al. (2017), Wei et al. (2017)
3	Dijkstra Algorithm	Basit et al. (2017)
4	Bayesian Optimization Algorithm	Dong and Chen (2018)
5	Mixed Integer Quadratic Programming	Killian et al. (2018)
6	Mixed Integer Linear Programming	Yao et al. (2017), Melhem et al. (2017), Marzband et al. (2017), Hao et al. (2017), Nizami and Hossain (2017)
7	Harmony Search Algorithm (HSA)	Zafar et al. (2017)
8	Bacterial Foraging Optimization (BFO)	Zafar et al. (2017), Javaid et al. (2017)
9	Enhanced Differential Evolution(EDE)	Zafar et al. (2017)
10	Genetic Algorithm	Javaid et al. (2017)
11	Binary Particle Swarm Optimization (BPSO)	Javaid et al. (2017)
12	Wind Driven Optimization (WDO)	Javaid et al. (2017)
13	Genetic BPSO (GBPSO)	Javaid et al. (2017)
14	Mixed Integer Non Linear Programming	Multi Objective Home Energy Management (MOHEM) using Cooperative Game Theory Lokeshgupta and Sivasubramani (2019), Cumulative Algorithm Hemmati (2017)
15	Natural Aggregation Algorithm	Luo et al. (2019), Li et al. (2017)

In Table 1, a comparison of performance between HSA, EDE and BFA for different factors is presented from Zafar et al. (2017). The optimization techniques are placed according to their performance for the respective factors.

In Lokeshgupta and Sivasubramani (2019), cooperative game theory approach is proposed for optimizing a multiobjective SHEMS problem. The proposed SHEMS model deals with the optimization of two functions viz. reducing the cost of electricity purchased from the grid and reducing the peak load demand of the home.

Table 2 gives a summary of the optimization techniques implemented in the literature for scheduling the appliances in the smart home.

6. SHEMS communications

An SHEMS framework is supposed to communicate with various entities like internet, grid and appliances. This communication is required to forecast, analyse and predict the load of the smart home for reducing the energy costs. Communication in smart home can also be utilized for actuation or controlling, data exchange for trading, etc.

SHEMS utilizes internet for acquiring the environmental forecast of the next day. It also communicates with utilities to read price signals (Keshtkar & Arzanpour, 2017).

The appliance state at a given time is sensed and communicated to SHEMS by smart plugs in Zhai et al. (2018). The appliance state can be a single value (ON/OFF) or multistate (Zhai et al., 2018). Within the smart home, the communication technology used in Keshtkar and Arzanpour (2017) are Zigbee or Wifi, based on their performance, however, other technologies can also be utilized. The different communication techniques which can be used within SHEMS are mentioned and compared in Guang et al. (2017).

Other than these, the SHEMS needs to also communicate with renewable energy sources within the home and other SHEMS framework in the neighbourhood for neighbourhood energy management as presented in Celik et al. (2017a) and Monyei et al. (2018).

The SHEMS physical architecture has been discussed earlier, however, SHEMS can also have a communication-based architecture (Mokhtari et al., 2019) as shown in Figure 9.

In Mokhtari et al. (2019), similar to a Supervisory Control and Data Acquisition (SCADA) protocol system, the SHEMS communication system is layered into: Physical Layer, Fog Computing Layer, Network Layer, Cloud Computing Layer, Service Layer, Session Layer and Application Layer.

In Jaouhari et al. (2019), authors utilize the Representational State Transfer (REST) communication architecture for SHEMS communications. The smart home is able to communicate with various entities like health providers, energy providers, etc. The communication architecture in this paper constitutes Device Layer, Gateway Layer and Application and Service Layer.

A practical smart home application is presented in Karimi et al. (2019). A smart phone is used to control the working of the home through the use of sensors and actuators. The research work includes the use of Internet of Things (IoT), Web services and Android App. The three main aspects presented are: (1) Arduino Uno Wi-Fi platform is used for interoperability amongst actuators, sensors and communication protocols, (2) REST framework is used for accessing appliances and for exchange of data, and (3) Android App for the user to control home appliances from anywhere.

A machine to machine communication in SHEM is discussed in Niyato et al. (2011). The machine to machine communication is standardized by European Telecommunications Standards Institute (ETSI). The communication network is divided into device domain, network domain and application domain. The appliance status and power consumption in the smart home is introduced. Dynamic Programming is used to optimize SHEMS traffic concentration. Wireless communication technologies are proposed in Niyato et al. (2011).

A remote smart home management concept is introduced through mPower Remote Manager (mPRM) in Valtchev and Frankov (2002). The paper presents and discusses the mPRM architecture along with a practical application of Open Service Gateway Initiative (OSGi). It discusses various protocols and communication technologies.

7. Forecasting

Forecasting plays a very important role in optimal working of SHEMS. Forecasting can be done for RESs, appliance scheduling/load forecasting, trading, energy storage, etc.

RES forecasting along with a model to predict is presented in Celik et al. (2017b), Kikusato et al. (2018) and Elma et al. (2017). In Celik et al. (2017b), error in prediction is also modelled. Power from RES is generally predicted based on data available from internet through weather forecasts.

The forecasting of appliance scheduling or load consumption in a smart home is presented in Zhai et al. (2018), Jin et al. (2017), Chen et al. (2017) and Collotta and Pau (2017). Prediction of load consumption is covered in Killian et al. (2018). Load forecasting

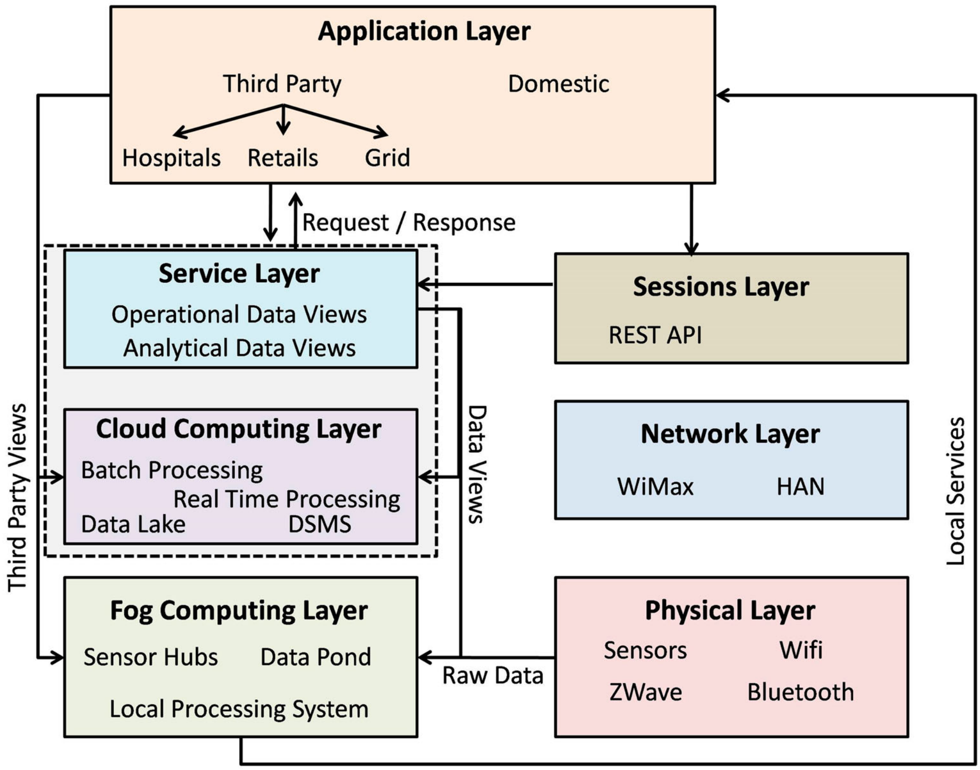

Figure 9. SHEMS Communication Layers in Mokhtari et al. (2019).

is combined with tariff prediction in Y. Liu et al. (2017). Tariff forecasting is also discussed in Najafi-Ghalelou et al. (2018) and Feron and Monti (2017).

In Jeddi et al. (2017) and Lorestani et al. (2017), RES as well as load predictions models are used. Thermal load prediction is also covered in Lorestani et al. (2017). Power generation from PV is forecasted for trading purposes in El-Baz et al. (2019).

Energy storage systems can be optimally utilized in an SHEMS through forecasting. The storage system may be batteries, EV, thermal, etc. The storage system is utilized in an SHEMS to implement the DR techniques and for shifting appliance schedule. Storage system is useful for improving reliability of power supply, storing excess power generated by RES, providing power for trading during peak tariff hours, etc. In some papers like Lorestani et al. (2017), it is assumed that the electrical energy can supply for thermal loads.

A simple battery storage system or EV used as storage is considered in Killian et al. (2018), Jin et al. (2017), Zunnurain and Maruf (2017), Celik et al. (2017a, 2017b), Jeddi et al. (2017), Wei et al. (2017), Yassein (2018), Lorestani et al. (2017), Dong and Chen (2018), Kikusato et al. (2018), Mondal et al. (2017), whereas thermal storage is also considered in Killian et al. (2018).

8. Energy trading and tariff

The renewable energy sources and energy storage systems will be an essential part of a smart home. The energy generated or stored can be utilized to reduce the energy bill through appliance scheduling or trading of energy. The smart home consumer plays an active role in the electric grid and is therefore now termed as prosumer (Morstyn & McCulloch, 2018; Sousa et al., 2019). It is more attractive now for a prosumer to trade electricity through a peer-to-peer (P2P) model rather than peer-to-grid (P2G) model (Long et al., 2018a, 2018b). The P2P trading also introduces a collective smart home environment aggregating into a neighbourhood energy management system. These neighbourhoods can be a building or locality, etc. The objectives of these neighbourhood energy management systems are to optimize the use and generation of RES, storage capabilities, reduction of overall cost of energy or alike for the neighbourhood.

The RES installations can be provided/created at the community level itself. The optimal appliance scheduling or EV charging can also be extended to the neighbourhood such that the load profile of the neighbourhood is flat. The tariff profile can also be generated for a particular locality, based on their mutual usage of energy. The control of these neighbourhood energy management systems is usually considered as decentralized in majority of research papers with each SHEMS trying to optimize its own benefit while still trying to achieve a common goal. Some of the research papers considering implementation of SHEMS into neighbourhood are Celik et al. (2017a, 2017b), Monyei et al. (2018), Kikusato et al. (2018), Mondal et al. (2017), Long et al. (2018b). A review on various markets related to community based trading is presented in Sousa et al. (2019).

The introduction of blockchain technique in energy trading at P2P level is considered in Mengelkamp et al. (2018) for opening up of decentralized markets. The blockchain business model along with Internet of Things (IoT) for prosumers is also discussed in Hwang et al. (2017). Different P2P business models are evaluated in Zhou et al. (2018) which are based on multiagent simulation framework. A blockchain-based P2P electricity trading amongst households is presented in Murkin et al. (2016).

An improved PV energy consumption is realized in N. Liu et al. (2017) through a business model based on economic cost and user's willingness. A real-time and forward market prosumer market is presented in El-Baz et al. (2019) in which consumer preference and privacy is considered. A decentralized SHEMS and device-oriented bidding strategy helps easy integration of appliances from various manufacturers. The power generation from PV is forecasted and integrated into the trading market which helps commitment from prosumers in forward markets. In Morstyn and McCulloch (2018), a receding horizon model is implemented for trading based on wholesale energy price, renewable energy generation and load forecasting. An energy sharing coordinator is supposed to control the energy resources of a smart home for trading of energy in Long et al. (2018b).

The energy trading market is based on different market models like bill sharing (Long et al., 2017), mid-market rate (Long et al., 2017), bilateral contract (Y. Liu et al., 2019) and auction-based pricing strategy (Y. Liu et al., 2019; Long et al., 2017). A customer to customer energy trading model is introduced in Zhang et al. (2016).

Tariff plays a very important role in optimizing the SHEMS framework. There are various tariff structures in place like simple rate, block rate, time of use, dynamic pricing, etc. Out of these some tariff structures do not play a part when energy trading is considered or when battery storage optimization is the objective.

The research papers using various tariff structures are:

- simple tariff – Jeddi et al. (2017), Monyei et al. (2018)

- dynamic pricing – Killian et al. (2018), Celik et al. (2017a, 2017b), Jeddi et al. (2017), Dong and Chen (2018), Basit et al. (2017), Keshtkar and Arzanpour (2017), Mondal et al. (2017)
- time of use – Yener et al. (2017), Jeddi et al. (2017), Yao et al. (2017), Kikusato et al. (2018),
- maximum demand – Ertugrul et al. (2017)

The variations between dynamic/real time pricing and time of use tariff is explained in Hogan (2014).

9. Discussion and analysis of factors in SHEMS

In this section, an analysis of different factors which are connected with the performance of SHEMS is performed. A large number of research papers have been summarized including those papers which are not listed in the references. Since SHEMS has a large number of reference and research papers, it is not possible to include all of them as references, however, many of the papers were referred for the analysis presented in this section.

Table 3 shows the percentage of papers addressing different factors of SHEMS. The first factor 'Tariff' stands for all the different types of tariffs except the simple rate tariff. The second factor is the 'BESS' that shows whether the SHEMS has BESS or not. The third factor points to the use of 'EV' as a part of SHEMS. EV could have been used as a storage or a load in the SHEMS. The fourth and fifth factors deal with the availability of renewable energy sources, i.e. 'PV' and 'Wind' in SHEMS respectively. The sixth factor is the consideration of 'UC' in SHEMS. The UC can be the privacy of the user, appliance waiting time, thermal comfort, etc. The seventh and eighth factors deal with the forecasting of load and generation in the SHEMS. The forecasting should be required for the operation of SHEMS, even though it may not have been calculated in the research paper to be included in these factors. The ninth factor introduces the usage of trading between the household and the grid. The last factor deals with monitoring of load in the home. This monitoring could be done through equipments, i.e. hardware or through the proposed software.

From Table 3, it can be concluded that Wind as a renewable source of energy in the SHEMS is not being considered in a wide variety of publications. The presence of BESS, PV and a non-simple rate Tariff system is the most widely researched topic, with more than 50% of the papers including these factors as part of their research applications. It was also observed that around 4% of papers also included fuel cells in some or the

Table 3. Factors affecting SHEMS in percentage of publications.

S. No.	Factor	Percentage
1	Tariff	72.54902
2	BESS	64.70588
3	EV	33.33333
4	PV	68.62745
5	Wind	19.60784
6	User Comfort(UC)	35.29412
7	Load	33.33333
8	Gen	23.52941
9	Trading	37.2549
10	Monitoring Load	39.21569

Table 4. Combination of factors affecting SHEMS in percentage of publications.

S. no.	Factor combinations	Percentage
1	BESS but 'NO' EV	43.137255
2	EV but 'NO' BESS	11.764706
3	Neither BESS 'NOR' EV	17.6471
4	Both BESS and EV	21.5686
4	PV but 'NO' WIND	50.9804
5	WIND but 'NO' PV	1.9608
6	'NO' RES	23.5294
7	Both PV and Wind	17.6471
8	Load Forecast but 'NO' Generation Forecast	9.8039
9	Generation Forecast but 'NO' Load Forecast	3.9216
10	'NO' Forecast	62.7451
11	Both Load and Generation Forecast	17.6471

other way. A similar percentage of publications had electrical energy price forecasting in their proposed models. Another factor which needs mention here is thermal storage which made up around 10% with hardware models also accounting for similar percentage.

An interesting analysis of the combination of these factors present in the SHEMS models is shown in Table 4. It can be observed that the majority of the SHEMS models are void of the forecasting feature. SHEMS have more PV panels with negligible Wind components. However, one very important feature that can be observed is that the presence of variation in SHEMS is less than a quarter strong, like both BESS and EV (21.6%), both PV and Wind (17.6%) and both Load and Generation Forecasting (17.6%).

The maximum number of factors that were a part of SHEMS structure were 8 in which UC and monitoring were not present, whereas the minimum number of factors included in a research work were 2 with UC and Tariff and another one with BESS and PV. The average factors covered in a publication were 4.27.

For better understanding and representation, the factors were reduced to 6, namely: Tariff, Storage, RES, UC, Forecast and Trading. Storage includes BESS and EV, RES covered any kind of renewable generation source, Forecast includes any type forecasting and Monitoring was removed as it mainly featured with hardware models. Table 5 presents a short analysis for the combination amongst these factors. Approximately 6% publications cover all the factors now. It was found that if a research work has forecasting in its SHEMS model then it would also have storage and the same applied for trading as well. For around 25.5% publications, they had a combination of Storage, Forecasting and Trading, with RES being in all of them by default.

An overlapping combination of Tariff, Storage, RES and UC in percentage is presented in Figure 10.

Table 5. Combination of reduced factors in SHEMS publications.

S. no.	Reduced factor combinations	Percentage
1	Tariff + RES + Storage + UC + Forecasting + Trading	5.8824
2	Forecast + Storage	37.2549
3	Trading + Storage	37.2549
4	Storage + Forecast + Trading (+ RES)	25.4902
5	Tariff + RES + Storage	52.9412
6	RES + Storage	68.6275

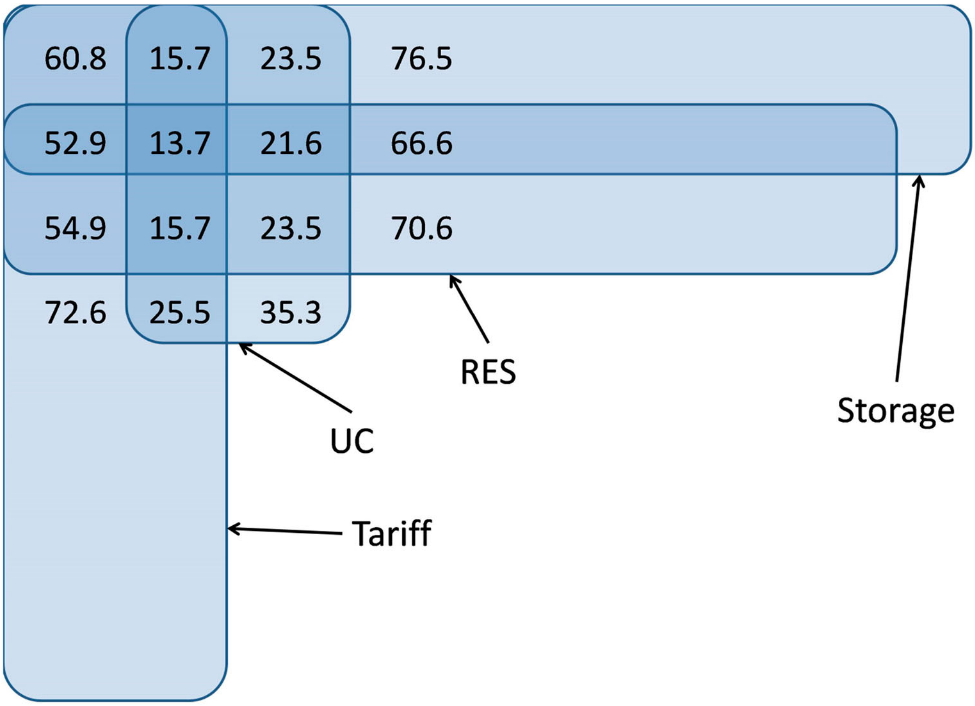

Figure 10. Tariff, storage, RES and user comfort percentages.

The objectives of the literature under consideration were classified into four categories: UC, Cost Reduction, Cost Reduction and UC and Others. The distribution of these objectives across the collection of research papers is presented in Figure 11. The publications having only UC as their objective accounted for around 2% while cost optimization was the main objective of around 63% of the publications. Another 23% of the publications have put in their efforts to optimize a multiobjective problem of Cost and UC. Other objectives like accurate monitoring/forecasting, etc. of SHEMS measured up to approximately 12%.

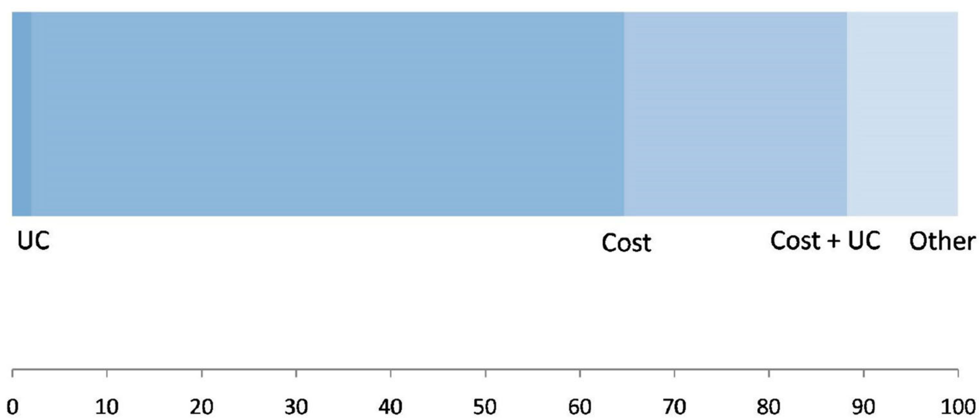

Figure 11. Objective distribution.

10. Conclusion

Electrical energy is the most important entity in our daily lives. Its demand has been increasing exponentially over a period now. The solution to more demand of energy is not to increase the power generation, but smart consumption of energy. The residential load can be smartly handled by placing a proper and adaptable SHEMS for handling these loads.

There are multiple factors that affect the optimal working of an SHEMS. The paper mentions, discusses and analyses these factors in depth, while trying to indicate the areas of research in SHEMS which require more attention. The SHEMS should be adaptable according to the location, occupant behaviour, environment, tariff, etc. The main objective of an SHEMS may vary from cost of energy consumed to UC and going on to create a multiobjective optimization problem including both.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Altaf Q. H. Badar http://orcid.org/0000-0002-1572-3717
Amjad Anvari-Moghaddam http://orcid.org/0000-0002-5505-3252

References

Abubakar, I., Khalid, S. N., Mustafa, M. W., Shareef, H., & Mustapha, M. (2017). Application of load monitoring in appliances' energy management: A review. *Renewable and Sustainable Energy Reviews*, *67*, 235–245. https://doi.org/10.1016/j.rser.2016.09.064

Ahmad, A., Khan, A., Javaid, N., Hussain, H. M., Abdul, W., Almogren, A., Alamri, A., & Azim Niaz, I. (2017). An optimized home energy management system with integrated renewable energy and storage resources. *Energies*, *10*(4), 549–583. https://doi.org/10.3390/en10040549

Basit, A., G. A. S. Sidhu, Mahmood, A., & Gao, F. (2017). Efficient and autonomous energy management techniques for the future smart homes. *IEEE Transactions on Smart Grid*, *8*(2), 917–926. https://doi.org/10.1109/TSG.2015.2504560

CEA. 2020. Growth of electricity sector in India from 1947–2019. http://www.cea.nic.in/reports/others/planning/pdm/growth_2019.pdf

Celik, B., Roche, R., Bouquain, D., & Miraoui, A. (2017a). Coordinated home energy management in community microgrids with energy sharing among smart homes. In *Electrimacs 2017* (p. 6p).

Celik, B., Roche, R., Bouquain, D., & Miraoui, A. (2017b). Decentralized neighborhood energy management with coordinated smart home energy sharing. *IEEE Transactions on Smart Grid*. https://doi.org/10.1109/TSG.2017.2710358

Chawda, K., Paul, T., Waris, J., & Badar, A. (2017). Fuzzy logic based short-term load forecasting. *International Journal of Innovative Research in Science, Engineering and Technology*, *6*(2), 1594–1599. https://doi.org/10.15680/IJIRSET.2017.0602024

Chen, S., Liu, T., Gao, F., Ji, J., Xu, Z., Qian, B., Wu, H., & Guan, X. (2017). Butler, not servant: A human-centric smart home energy management system. *IEEE Communications Magazine*, *55*(2), 27–33. https://doi.org/10.1109/MCOM.2017.1600699CM

Collotta, M., & Pau, G. (2017). An innovative approach for forecasting of energy requirements to improve a smart home management system based on BLE. *IEEE Transactions on Green Communications and Networking*, *1*(1), 112–120. https://doi.org/10.1109/TGCN.2017.2671407

Dong, G., & Chen, Z. (2018). Data driven energy management in a home microgrid based on Bayesian optimal algorithm. *IEEE Transactions on Industrial Informatics*. https://doi.org/10.1109/TII.2018.2820421

El-Baz, W., Tzscheutschler, P., & Wagner, U. (2019). Integration of energy markets in microgrids: A double-sided auction with device-oriented bidding strategies. *Applied Energy*, *241*, 625–639. https://doi.org/10.1016/j.apenergy.2019.02.049

Elma, O., Taşcıkaraoğlu, A., İnce, A. T., & Selamoğulları, U. S. (2017). Implementation of a dynamic energy management system using real time pricing and local renewable energy generation forecasts. *Energy*, *134*, 206–220. https://doi.org/10.1016/j.energy.2017.06.011

Energy Consumption By Country 2020 [Computer software manual]. 2020. https://worldpopulationreview.com/countries/energy-consumption-by-country/

Ertugrul, N., McDonald, C. E., & Makestas, J. (2017). Home energy management system for demand-based tariff towards smart appliances in smart grids. In *2017 IEEE 12th international conference on power electronics and drive systems (PEDS)* (pp. 511–517). IEEE.

Faustine, A., Mvungi, N. H., Kaijage, S., & Michael, K. (2017). A survey on non-intrusive load monitoring methods and techniques for energy disaggregation problem. Preprint arXiv:1703.00785.

Feron, B., & Monti, A. (2017). Integration of space heating demand flexibility in a home energy management system using a market-based multi agent system. In *Power & energy society general meeting, 2017 IEEE* (pp. 1–5). IEEE.

Guang, N. L. L., Logenthiran, T., & Abidi, K. (2017). Application of Internet of Things (IoT) for home energy management. In *Asia-pacific power and energy engineering conference (APPEEC), 2017 IEEE PES* (pp. 1–6). IEEE.

Hao, Y., Wang, W., & Qi, Y. (2017). Optimal home energy management with PV system in time of use tariff environment. In *Chinese automation congress (CAC), 2017* (pp. 2693–2697). IEEE.

Hemmati, R. (2017). Technical and economic analysis of home energy management system incorporating small-scale wind turbine and battery energy storage system. *Journal of Cleaner Production*, *159*, 106–118. https://doi.org/10.1016/j.jclepro.2017.04.174

Hogan, W. W. (2014). *Time-of-use rates and real-time prices*. John F. Kennedy School of Government, Harvard University.

Hwang, J., Choi, M i., Lee, T., Jeon, S., Kim, S., Park, S., & Park, S. (2017). Energy prosumer business model using blockchain system to ensure transparency and safety. *Energy Procedia*, *141*, 194–198. https://doi.org/10.1016/j.egypro.2017.11.037

Jaouhari, S. E., Palacios-Garcia, E. J., Anvari-Moghaddam, A., & Bouabdallah, A. (2019). Integrated management of energy, wellbeing and health in the next generation of smart homes. *Sensors*, *19*(3), 481. https://doi.org/10.3390/s19030481

Javaid, N., Naseem, M., Rasheed, M. B., Mahmood, D., Khan, S. A., Alrajeh, N., & Iqbal, Z. (2017). A new heuristically optimized Home Energy Management controller for smart grid. *Sustainable Cities and Society*, *34*, 211–227. https://doi.org/10.1016/j.scs.2017.06.009

Jeddi, B., Mishra, Y., & Ledwich, G. (2017). Dynamic programming based home energy management unit incorporating PVs and batteries. In *Power & energy society general meeting, 2017 IEEE* (pp. 1–5). IEEE.

Jin, X., Baker, K., Christensen, D., & Isley, S. (2017). Foresee: A user-centric home energy management system for energy efficiency and demand response. *Applied Energy*, *205*, 1583–1595. https://doi.org/10.1016/j.apenergy.2017.08.166

Kang, J. W., Xie, L., & Choi, D. H. (2018). Impact of data quality in home energy management system on distribution system state estimation. *IEEE Access*, *6*, 11024–11037. https://doi.org/10.1109/Access.6287639

Karimi, K., Oudani, H., & Krit, S. (2019). RESTful web services based communication for smart home smartphone systems. *Journal of Advanced Research in Dynamical and Control Systems*, 11 (Special Issue 02), 1660–1667.

Keshtkar, A., & Arzanpour, S. (2017). An adaptive fuzzy logic system for residential energy management in smart grid environments. *Applied Energy*, *186*, 68–81. https://doi.org/10.1016/j.apenergy.2016.11.028

Kikusato, H., Mori, K., Yoshizawa, S., Fujimoto, Y., Asano, H., Hayashi, Y., & Suzuki, T. (2018). Electric vehicle charge-discharge management for utilization of photovoltaic by coordination between home and grid energy management systems. *IEEE Transactions on Smart Grid*, 10, 3186–3197. https://doi.org/10.1109/TSG.2018.2820026

Killian, M., Zauner, M., & Kozek, M. (2018). Comprehensive smart home energy management system using mixed-integer quadratic-programming. *Applied Energy*, *222*, 662–672. https://doi.org/10.1016/j.apenergy.2018.03.179

Li, C., Luo, F., Chen, Y., Xu, Z., An, Y., & Li, X. (2017). Smart home energy management with vehicle-to-home technology. In *2017 13th IEEE international conference on control & automation (ICCA)* (pp. 136–142). IEEE.

Liu, N., Yu, X., Wang, C., Li, C., Ma, L., & Lei, J. (2017). Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers. *IEEE Transactions on Power Systems*, *32*(5), 3569–3583. https://doi.org/10.1109/TPWRS.2017.2649558

Liu, Y., Wu, L., & Li, J. (2019). Peer-to-peer (P2P) electricity trading in distribution systems of the future. *The Electricity Journal*, *32*(4), 2–6. https://doi.org/10.1016/j.tej.2019.03.002

Liu, Y., Zhang, Y., Chen, K., Chen, S. Z., & Tang, B. (2017). Equivalence of multi-time scale optimization for home energy management considering user discomfort preference. *IEEE Transactions on Smart Grid*, *8*(4), 1876–1887. https://doi.org/10.1109/TSG.2015.2510222

Lokeshgupta, B., & Sivasubramani, S. (2019). Cooperative game theory approach for multi-objective home energy management with renewable energy integration. *IET Smart Grid*, *2*(1), 34–41. https://doi.org/10.1049/iet-stg.2018.0094

Long, C., Wu, J., Zhang, C., Thomas, L., Cheng, M., & Jenkins, N. (2017). Peer-to-peer energy trading in a community microgrid. In *2017 IEEE power & energy society general meeting* (pp. 1–5). IEEE.

Long, C., Wu, J., Zhou, Y., & Jenkins, N. (2018a, January). Aggregated battery control for peer-to-peer energy sharing in a community Microgrid with PV battery systems. *Energy Procedia*, *145*, 522–527. https://doi.org/10.1016/j.egypro.2018.04.076

Long, C., Wu, J., Zhou, Y., & Jenkins, N. (2018b, February). Peer-to-peer energy sharing through a two-stage aggregated battery control in a community Microgrid. *Applied Energy*, *226*, 261–276. https://doi.org/10.1016/j.apenergy.2018.05.097

Lorestani, A., Aghaee, S. S., Gharehpetian, G. B., & Ardehali, M. M. (2017). Energy management in smart home including PV panel, battery, electric heater with integration of plug-in electric vehicle. In *Smart grid conference (SGC), 2017* (pp. 1–7).

Luo, F., Kong, W., Ranzi, G., & Dong, Z. Y. (2019). Optimal home energy management system with demand charge tariff and appliance operational dependencies. *IEEE Transactions on Smart Grid*, *11*(1), 4–14. https://doi.org/10.1109/TSG.5165411

Marzband, M., Alavi, H., Ghazimirsaeid, S. S., Uppal, H., & Fernando, T. (2017). Optimal energy management system based on stochastic approach for a home Microgrid with integrated responsive load demand and energy storage. *Sustainable Cities and Society*, *28*, 256–264. https://doi.org/10.1016/j.scs.2016.09.017

Melhem, F. Y., Grunder, O., Hammoudan, Z., & Moubayed, N. (2017). Optimization and energy management in smart home considering photovoltaic, wind, and battery storage system with integration of electric vehicles. *Canadian Journal of Electrical and Computer Engineering*, *40*(2), 128–138. https://doi.org/10.1109/CJECE.2017.2716780

Mengelkamp, E., Notheisen, B., Beer, C., Dauer, D., & Weinhardt, C. (2018). A blockchain-based smart grid: Towards sustainable local energy markets. *Computer Science - Research and Development*, *33*(1-2), 207–214. https://doi.org/10.1007/s00450-017-0360-9

Mokhtari, G., Anvari-Moghaddam, A., & Zhang, Q. (2019). A new layered architecture for future big data-driven smart homes. *Ieee Access*, *7*, 19002–19012. https://doi.org/10.1109/ACCESS.2019.2896403

Mondal, A., Misra, S., & Obaidat, M. S. (2017). Distributed home energy management system with storage in smart grid using game theory. *IEEE Systems Journal*, *11*(3), 1857–1866. https://doi.org/10.1109/JSYST.2015.2421941

Monyei, C. G., Adewumi, A. O., Akinyele, D., Babatunde, O. M., Obolo, M. O., & Onunwor, J. C. (2018). A biased load manager home energy management system for low-cost residential building low-income occupants. *Energy*, *150*, 822–838. https://doi.org/10.1016/j.energy.2018.03.016

Morstyn, T., & McCulloch, M. (2018). Multi-class energy management for peer-to-peer energy trading driven by prosumer preferences. *IEEE Transactions on Power Systems*, *34*, 4005–4014, https://doi.org/10.1109/TPWRS.2018.2834472

Murkin, J., Chitchyan, R., & Byrne, A. (2016). Enabling peer-to-peer electricity trading. In *ICT for sustainability 2016*. Atlantis Press. https://doi.org/10.2991/ict4s-16.2016.30

Najafi-Ghalelou, A., Nojavan, S., & Zare, K. (2018). Information gap decision theory-based risk-constrained scheduling of smart home energy consumption in the presence of solar thermal storage system. *Solar Energy*, *163*, 271–287. https://doi.org/10.1016/j.solener.2018.02.013

Niyato, D., Lu, X., & Wang, P. (2011). Machine-to-machine communications for home energy management system in smart grid. *IEEE Communications Magazine*, *49*(4), 53–59. https://doi.org/10.1109/MCOM.2011.5741146

Nizami, M. S. H., & Hossain, J. (2017). Optimal scheduling of electrical appliances and DER units for home energy management system. In *Universities power engineering conference (AUPEC), 2017 Australasian* (pp. 1–6). IEEE.

Pawar, P., & Vittal, K. (2017). Design of smart socket for power optimization in home energy management system. In *2017 2nd IEEE international conference on recent trends in electronics, information & communication TECHNOLOGY (rteict)* (pp. 1739–1744). IEEE.

Ridi, A., Gisler, C., & Hennebert, J. (2014). A survey on intrusive load monitoring for appliance recognition. In *2014 22nd international conference on pattern recognition* (pp. 3702–3707). IEEE.

Sousa, T., Soares, T., Pinson, P., Moret, F., Baroche, T., & Sorin, E. (2019). Peer-to-peer and community-based markets: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *104*, 367–378. https://doi.org/10.1016/j.rser.2019.01.036

Valtchev, D., & Frankov, I. (2002). Service gateway architecture for a smart home. *IEEE Communications Magazine*, *40*(4), 126–132. https://doi.org/10.1109/35.995862

Wei, Q., Lewis, F. L., Shi, G., & Song, R. (2017). Error-tolerant iterative adaptive dynamic programming for optimal renewable home energy scheduling and battery management. *IEEE Transactions on Industrial Electronics*, *64*(12), 9527–9537. https://doi.org/10.1109/TIE.2017.2711499

Wu, X., Hu, X., Moura, S., Yin, X., & Pickert, V. (2016). Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array. *Journal of Power Sources*, *333*, 203–212. https://doi.org/10.1016/j.jpowsour.2016.09.157

Yao, L., Damiran, Z., & Lim, W. H. (2017). Energy management optimization scheme for smart home considering different types of appliances. In *2017 IEEE international conference on environment and electrical engineering and 2017 IEEE industrial and commercial power systems Europe (EEEIC/I&CPS Europe)* (pp. 1–6). IEEE.

Yassein, M. B. (2018). Enhanced home energy management scheme (EHEM) in smart grids. *International Journal of Communication Networks and Information Security (IJCNIS)*, *10*(1), 85–90. Kohat University of Science and Technology (KUST).

Yener, B., Taşçıkaraoğlu, A., Erdinç, O., Baysal, M., & Catalão, J. P. (2017). Design and implementation of an interactive interface for demand response and home energy management applications. *Applied Sciences*, *7*(6), 641. https://doi.org/10.3390/app7060641

Zafar, A., Shah, S., Khalid, R., Hussain, S. M., Rahim, H., & Javaid, N. (2017). A meta-heuristic home energy management system. In *2017 31st international conference on advanced information networking and applications workshops (WAINA)* (pp. 244–250). IEEE.

Zhai, S., Wang, Z., Yan, X., & He, G. (2018). Appliance flexibility analysis considering user's behavior in home energy management system using smart plugs. *IEEE Transactions on Industrial Electronics*, *66*, 1391–1401, https://doi.org/10.1109/TIE.2018.2815949

Zhang, C., Wu, J., Cheng, M., Zhou, Y., & Long, C. (2016). A bidding system for peer-to-peer energy trading in a grid-connected microgrid. *Energy Procedia*, *103*, 147–152. https://doi.org/10.1016/j.egypro.2016.11.264

Zhou, Y., Wu, J., & Long, C. (2018). Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework. *Applied Energy*, *222*, 993–1022. https://doi.org/10.1016/j.apenergy.2018.02.089

Zunnurain, I., & Maruf, M. N. I. (2017). Automated demand response strategies using home energy management system in a RES-based smart grid. In *2017 4th international conference on advances in electrical engineering (ICAEE)* (pp. 664–668). IEEE.