



Learning-Based Energy Management System for Scheduling of Appliances inside Smart Homes

N. Gholizadeh¹, M. Abedi², H. Nafisi^{2,*}, M. Marzband³

¹ M.Sc., Department of Electrical Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran.

² Ph.D., Department of Electrical Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran.

³ Ph.D., Department of Mathematics, Physics and Electrical Engineering

ABSTRACT: Improper designs of the demand response programs can lead to numerous problems such as customer dissatisfaction and lower participation in these programs. In this paper, a home energy management system is designed which schedules appliances of smart homes based on the user's specific behavior to address these issues. Two types of demand response programs are proposed for each house which are shifting-based and learning-based programs for shiftable and heating, ventilation and cooling appliances, respectively. The current structure uses machine learning techniques to design the best demand response programs for heating, ventilation and cooling devices of each user based on his/her behavior and desired comfort level. Doing so, the home energy management system is able to achieve energy cost and consumption reduction without causing dissatisfaction and discomfort to the users. Results demonstrate that by using this structure, energy cost and consumption are reduced by 20.32% and 27%, respectively for a single house located in the Austin, Texas area, in one day. The proposed home energy management structure is tested on three additional houses to show the effectiveness of it. Moreover, comparisons with other methods are performed to clarify the benefits of this structure over other methods. The proposed structure is formulated as a mixed-integer linear model with its optimization performed in the General Algebraic Modeling System environment. CPLEX solver is used to solve the optimization problem.

Review History:

Received: 2019-08-08

Revised: 2019-09-22

Accepted: 2019-10-12

Available Online: 2019-12-01

Keywords:

Demand response

Home energy management system

Machine learning

Mixed-integer linear programming

User behavior

1. INTRODUCTION

Introduction of the smart homes in the recent years has heightened the need for an efficient home energy management system (HEMS) which can communicate with the appliances and upper grid to perform demand response (DR) and schedule the consumption [1, 2]. A HEMS consists of software, hardware and communication protocols like Wi-Fi and Zigbee and acts as the control center inside a house [3]. Also, it can decide about the participation of the smart home in DR programs by receiving the information from the upper grid and home appliances and performing optimization [4, 5].

Intensive research has been conducted in the literature regarding DR management by HEMS. In [6], demand response programs have been used inside a smart home to reduce energy costs and increase the utilization of renewable energy resources. A DR management system for smart homes has been presented in [7], which is based on minority game and reduces demand peak while fairly allocating the solar energy on the additional grid. Restricted and multi-restricted scheduling methods have been used in [8], for scheduling the appliances of smart homes by HEMS. For the optimization

*Corresponding author's email: nafisi@aut.ac.ir

process grey wolf optimizer (GWO) has been utilized. To increase renewable uptake and decrease customers' electricity bill, an intelligent battery control combined with solar generation inside HEMS has been proposed in [9] which also has considered consumer comfort. In [10], a versatile convex programming DR optimization framework has been used to automatically manage the different appliances inside a household. Operation of several classes of home appliances like deferrable, curtailable, thermal and critical ones has been managed by a HEMS in [11], using DR programs to reduce consumer's electricity bill and minimize daily curtailed energy. A joint scheduling scheme for the electric supply and demand of HEMS has been presented in [12] to reduce electricity bill. Stochastic model of a HEMS has been presented by [13] which considers uncertainties of electric vehicles and generation of renewable energy resources and minimizes customer's cost and response fatigue. A multi-objective mixed-integer nonlinear programming model for HEMS has been proposed by [14], which performs appliance scheduling in a way to achieve a balance between energy saving and comfortable lifestyle. In [15], energy scheduling of a household equipped with solar-assisted heating, ventilation, and air conditioning,



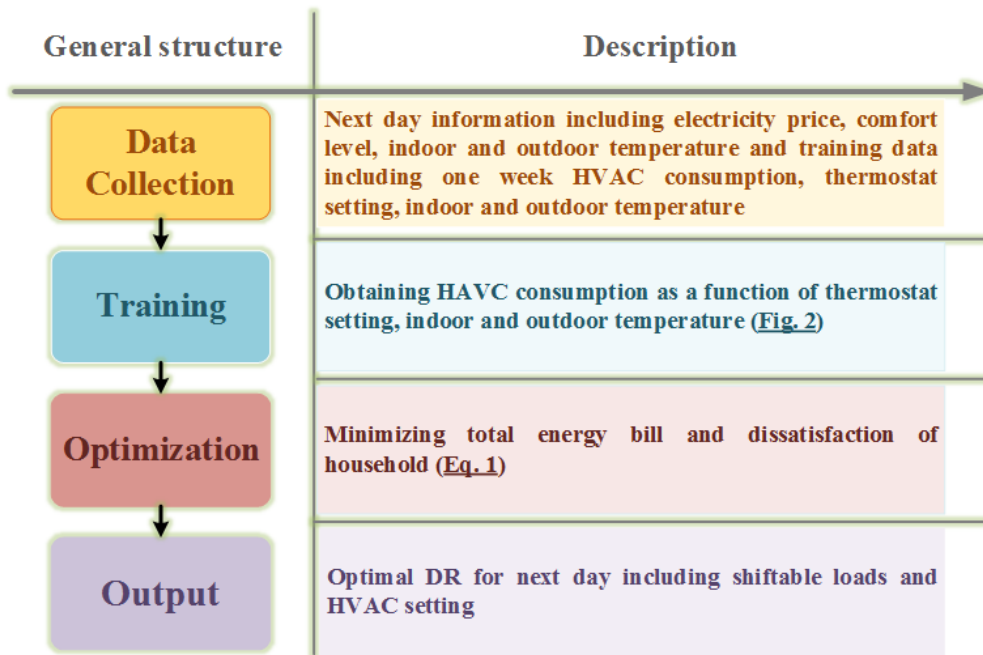


Fig. 1. Proposed HEMS structure

and water heating system has been performed to minimize energy cost and fulfill user's thermal comfort requirements. An intelligent algorithm for HEMS has been proposed in [16], which manages loads according to their preset priority and guarantees power consumption below certain levels. A distributed framework for DR has been developed in [17], which is based on cost minimization and is solved using an approximate greedy iterative algorithm.

Modeling user behavior to obtain the best DR program without causing dissatisfaction to customers is crucial. To this end, multiple studies have attempted to model user behavior using different techniques. In [18], user behavior has been grouped into two comfort-seeking behavior and green incentive seeking behavior. Stochastic models have been used in [19, 20] to take user behavior uncertainty into account. Also, in [21] and [22] user's behavior regarding thermal loads has been modeled using equivalent resistance-capacitance network and regression method, respectively. Energy consumption of the heating, ventilation and cooling (HVAC) systems has been modeled using the equivalent thermal parameters (ETP) in [23]. A novel learning-based method has been developed by [24], to model user behavior and DR regarding the HVAC systems. Modeling of user behavior is a complex problem due to the effects of seasonal changes, weather changes, personal habits, etc. on consumption pattern. The learning-based approach which is adopted from [24] is found to be the most accurate approach to model user behavior. Therefore, it is used in this paper to design the best DR program for users considering their HVAC consumption behavior. Moreover, a shifting-based DR is considered as well and the model is simplified as a mixed-integer linear model. In addition, the main contributions of this paper are as follows:

- Presenting a simplified mixed-integer linear model for HEMS of a smart home which considers user behavior;
- Considering two types of DR programs for home appliances which consist of learning-based and shifting-based DRs;
- Modeling user dissatisfaction in the objective function to prevent discomfort issues.

2. SYSTEM STRUCTURE

The proposed HEMS in this study is able to send and receive information from grid and individual appliances. It is also able to control the operation of the devices and perform DR based on the received information and the optimizations that it performs. The overall structure of the proposed HEMS is illustrated in Fig. 1. As can be seen, first, the data needed for the optimization and training process is obtained from the smart meter. This data includes next-day electricity price, desired comfort level, indoor and outdoor temperature for the optimization process and one-week HVAC consumption data, thermostat setting, indoor and outdoor temperature for the training process. Next, by using the one-week user data, training is performed to derive HVAC system's consumption model. At this stage, unsupervised machine learning technique is used to obtain HVAC consumption as a function of thermostat setting, indoor and outdoor temperature. A schematic of the proposed neural network structure is depicted in Fig. 2. For the training process, one-week thermostat setting, indoor and outdoor temperature data is given as the input to this neural network while the target data is one-week HVAC consumption. An iterative algorithm is implemented here which updates the weights (w_i) and biases of the neural network in each iteration to find the ideal weights

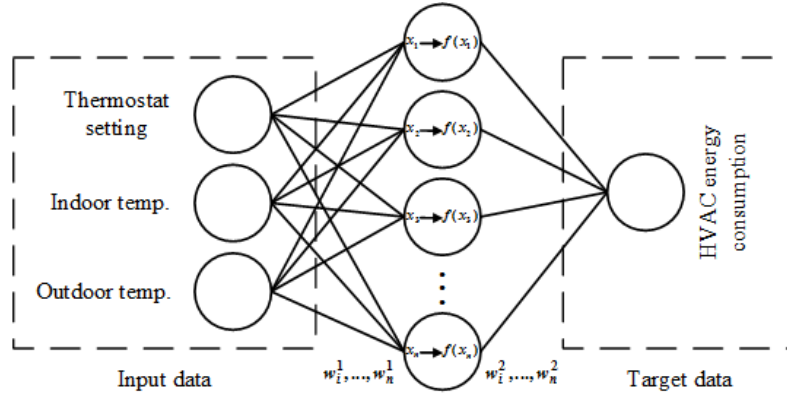


Fig. 2. Proposed neural network structure

and biases that can be used to model the target as a function of the input parameters. In order to simplify the HVAC model, Leaky Rectified Linear Unit (Leaky ReLU), shown by $f(x)$ in Fig. 2, is used as the activation function. In the third stage, optimization is performed by HEMS to minimize energy cost and user dissatisfaction and as a result of this optimization process, the best next-day DR program for user is obtained which includes best thermostat setting for HVAC systems and start time of shiftable loads.

3. PROBLEM FORMULATION

The formulation regarding the optimization process of the HEMS is presented in the following subsections.

3-1- Objective function

As mentioned before, the objective of the HEMS in this study is to minimize the energy bill and dissatisfaction of the electricity user. Therefore, the objective function of this optimization problem is formulated as Eq. (1). The energy cost which is presented by C_t^{Grid} is simply calculated by multiplying per kWh electricity price (π_t^e) in the bought power from the grid (P_t^{buy}) as in Eq. (2). As can be seen from Eq. (3), user dissatisfaction cost, which is represented by C_t^{DR} , consists of two terms that are dissatisfaction caused by shifting of loads and dissatisfaction caused by DR of HVAC loads.

$$OF = \min \sum C_t^{Grid} + C_t^{DR} \quad (1)$$

$$C_t^{Grid} = \pi_t^e P_t^{buy} \quad (2)$$

$$C_{t,h}^{DR} = d_{t,h}^{shift} + d_{t,h}^{hvac} \quad (3)$$

3-2- User dissatisfaction

In order to model the dissatisfaction caused to users by shifting of shiftable loads, Eq. (4) is used. Parameter α^{sh} shows the dissatisfaction cost per kWh of shifted loads. Also, t_{st} and $P_{t,t_{st}}^{shift}$ show the desired start time and shifted power of shiftable loads, respectively. Dissatisfaction cost of the HVAC

loads is calculated by Eq. (5) where β^{hvac} shows the overall desired comfort level of the user, P_t^{Fhvac} shows the forecasted power consumption of HVAC loads and P_t^{hvac} stands for the power consumption of these loads. Moreover, λ_t represents the hourly desired comfort level for the HVAC system and ranges between 0 to 1. Both models have been adopted from [25] and linearized using a piecewise linear function similar to [26].

$$d_t^{shift} = \sum_{t_{st}} \alpha^{sh} |t_{st} - t| P_{t,t_{st}}^{shift} \quad (4)$$

$$d_t^{hvac} = \beta^{hvac} (P_t^{Fhvac} \pi_t^e [1 - (\frac{P_t^{hvac}}{P_t^{Fhvac}})^{\lambda_t}]) \quad (5)$$

Two linear functions are used to linearize Eq. (5). For this purpose, Eq. (6) to Eq. (14) are introduced to the model. In Eq. (6), γ_t^1 and γ_t^2 are the equivalent slopes of the linear functions while ψ_t^1 and ψ_t^2 are the equivalent y-intercepts of these functions. These parameters are calculated by Eq. (7) to Eq. (10). P_t^{hvac} is divided into two intervals which are denoted by P_t^{hvac1} and P_t^{hvac2} for the first and second intervals, respectively. The binary variables I_t^{int1} and I_t^{int2} show the existence of HVAC operation point in the first or second interval, respectively.

$$d_t^{hvac} = \gamma_t^1 P_t^{hvac1} + \gamma_t^2 P_t^{hvac2} + \psi_t^1 I_t^{int1} + \psi_t^2 I_t^{int2} \quad (6)$$

$$\gamma_t^1 = -\beta^{hvac} \pi_t^e (\frac{1}{4})^{\lambda_t - 1} \quad (7)$$

$$\gamma_t^2 = -\beta^{hvac} \pi_t^e (\frac{3}{4})^{\lambda_t - 1} \quad (8)$$

$$\psi_t^1 = \beta^{hvac} P_t^{Fhvac} \pi_t^e (1 - (\frac{1}{4})^{\lambda_t}) - \frac{\gamma_t^1 P_t^{Fhvac}}{4} \quad (9)$$

$$\psi_t^2 = \beta^{hvac} P_t^{Fhvac} \pi_t^e (1 - (\frac{3}{4})^{I_t}) - \frac{3\gamma_t^2 P_t^{Fhvac}}{4} \quad (10)$$

As it was mentioned earlier, P_t^{hvac} is divided into two intervals therefore, Eq. (11) is introduced to model this relationship. Each of the Eq. (12) and Eq. (13) specify the upper and lower limit of these intervals. Also, Eq. (14) is introduced to prevent simultaneous operation of the HVAC in both intervals.

$$P_t^{hvac} = P_t^{hvac1} + P_t^{hvac2} \quad (11)$$

$$0 \leq P_t^{hvac1} \leq \frac{I_t^{int1} P_t^{Fhvac}}{2} \quad (12)$$

$$\frac{I_t^{int2} P_t^{Fhvac}}{2} \leq P_t^{hvac2} \leq I_t^{int2} P_t^{Fhvac} \quad (13)$$

$$0 \leq I_t^{int1} + I_t^{int2} \leq 1 \quad (14)$$

3-3- Energy balance constraint

The energy balance constraint, which is modeled by Eq. (15), states that the electricity power imported from the main grid should be equal to the power consumption of the loads inside the house. In this equation, P_t^{fixed} and P_t^{Tsh} show the total fixed and shiftable loads power consumption at each hour, respectively. Total used power of shiftable loads at each hour is calculated by Eq. (16). The binary variable $I_{t,tst}^{sh}$ shows whether a load has been shifted to or from the time t and parameter $P_t^{shiftable}$ is the power consumption of shiftable loads at each hour before performing DR.

$$P_t^{buy} = P_t^{fixed} + P_t^{hvac} + P_t^{Tsh} \quad (15)$$

$$P_t^{Tsh} = P_t^{shiftable} - \sum_{t_{st}} P_{t,t_{st}}^{shif} I_{t,t_{st}}^{sh} \quad (16)$$

3-4- Neural network weights

As it was mentioned in the previous section, a two-layer neural network structure is used to obtain the model of HVAC energy consumption as a function of thermostat setting, indoor and outdoor temperature. For this purpose, an iterative algorithm named back-propagation is used to update weights of this neural network in each iteration until the ideal weights for modeling with minimal error are found. The weights of this neural network are updated using Eq. (17) to Eq. (21). In Eq. (17), H_i^{out} shows the data values present in the hidden layer of the neural network in iteration i . These values are calculated by multiplying the weights of input-to-hidden-layer ($w_i^{inp-hid}$) in the inputs and giving the result to the activation function. In Eq. (18), ΔH_i^{out} is calculated for updating the weights and lr^1 shows the learning rate of the neural network. The error is simply calculated by subtracting the predicted output from the original one. Finally, the hidden-to-output-layer weights

($w_i^{hid-out}$) are updated by Eq. (19). In a similar way, Eq. (20) and Eq. (21) are used to update the input-to-hidden-layer weights where lr^2 shows the learning rate of this layer. The stop criteria used for this iterative algorithm is mean absolute percentage error (MAPE) which needs to be minimal. For the normalization of the input and output data min-max method is used.

$$H_i^{out} = ReLU(Input \times w_i^{inp-hid}) \quad (17)$$

$$\Delta H_i^{out} = lr^1 \times error \times H_i^{out} \quad (18)$$

$$w_{i+1}^{hid-out} = w_i^{hid-out} - \Delta H_i^{out} \quad (19)$$

$$\Delta H_i^{input} = lr^2 \times error \times w_i^{hid-out} \times Input \quad (20)$$

$$w_{i+1}^{inp-hid} = w_i^{inp-hid} - \Delta H_i^{input} \quad (21)$$

4. SIMULATION RESULTS AND DISCUSSION

The proposed formulation for the HEMS is applied to a smart home located in the Austin, Texas area. The data of the house is derived from Pecan Street Inc. [27]. Due to lack of HVAC thermostat setting data, it was set equal to next hour indoor temperature similar to [24]. The used neural network structure consists of one hidden layer with 25 neurons. The forecasted electricity price data is shown in Fig. 3 and the parameter values are given in Table 1. To show the effectiveness of the current HEMS system in reducing energy cost and usage two scenarios are defined as below:

- Scenario 1: Smart home with a HEMS
- Scenario 2: Smart home without a HEMS

The power consumption of the HVAC system is depicted in Fig. 4. It is evident from this Figure that the general trend of HVAC consumption is maintained and the proposed HEMS structure has successfully decreased the power consumption of HVAC systems without causing discomfort to users. For the hours that have a higher hourly desired comfort level, HVAC consumption with HEMS is equal to the consumption without HEMS.

Shiftable load values are illustrated in Fig. 5. Due to higher electricity price in 14th and 16th hour, most of the shiftable loads in this period are shifted to low price times like 10th and 12th hour. Since user dissatisfaction is also considered in this study, shiftable loads are not differed to the lowest price hours like the 3rd hour.

Total consumed power from the main grid is depicted in Fig. 6. As can be seen, the consumption pattern is changed as a result of both reduction and shifting of power consumption. Also, a reasonable tradeoff between reduction in consumption and user satisfaction is obtained.

Total cost and consumption reduction by using the current HEMS structure is given in Table 2. The current HEMS structure is able to save 22.3% and 33.3% in energy cost and consumption, respectively. Moreover, the user's desired comfort level is maintained and this structure has the flexibility to adapt to different user behaviors and comfort

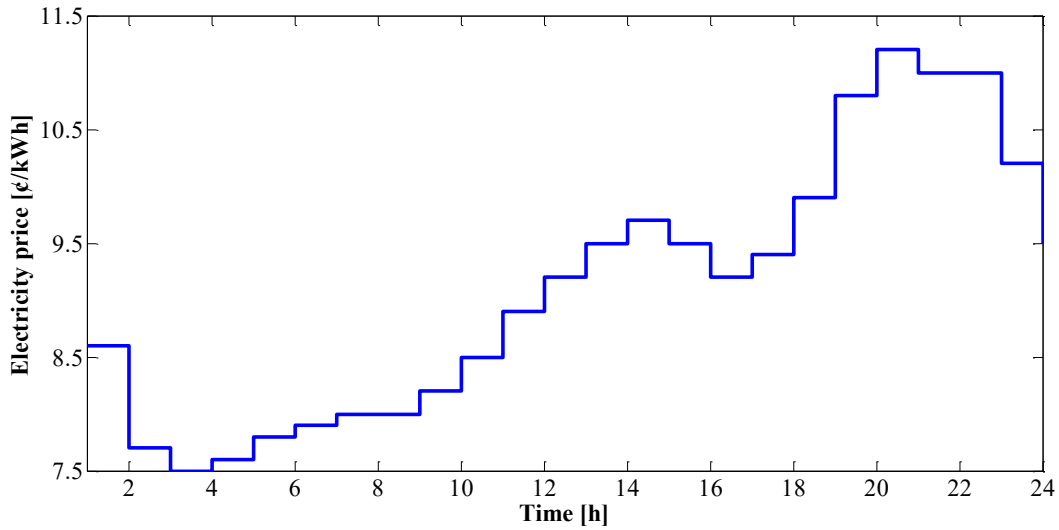


Fig. 3. Forecasted hourly electricity price

Table 1. Parameter values

α^{sh} [\$/kWh]	β^{hvac}	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	λ_{10}	λ_{11}
0.0001	4	0.51	0.35	0.32	0.30	0.22	0.33	0.27	0.14	0.02	0.15	0.16
λ_{12}	λ_{13}	λ_{14}	λ_{15}	λ_{16}	λ_{17}	λ_{18}	λ_{19}	λ_{20}	λ_{21}	λ_{22}	λ_{23}	λ_{24}
0.21	0.19	0.45	0.34	0.76	0.65	0.92	0.76	0.58	0.48	0.65	1.00	0.56

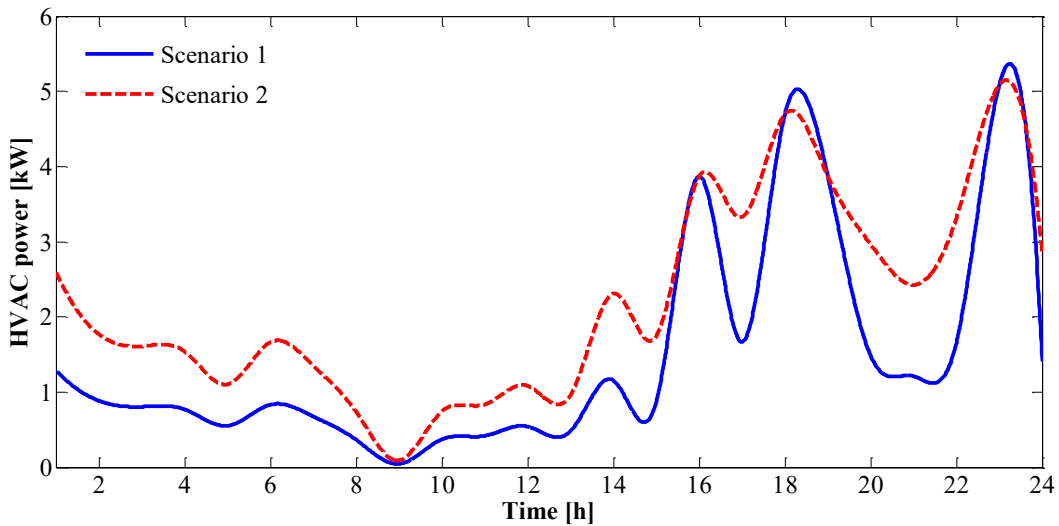


Fig. 4. Hourly HVAC energy consumption in two scenarios

levels or change in user behavior over time.

In order to demonstrate the advantages of the proposed method compared to other methods, three more case studies were studied. The first case has no DR program for HVAC devices. In the second case, no hourly and overall comfort

level is considered for HVAC consumers and therefore, the dissatisfaction caused to the consumers due to DR of HVACs is modeled as a linear function only. In the third case, only an upper and lower level for thermostat setting is considered to model user comfort similar to [24]. In general, the proposed

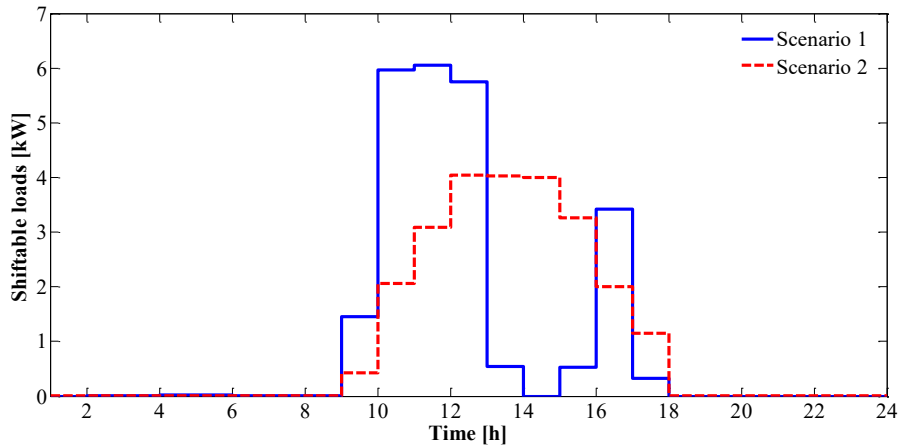


Fig. 5. Hourly shiftable load values in two scenarios

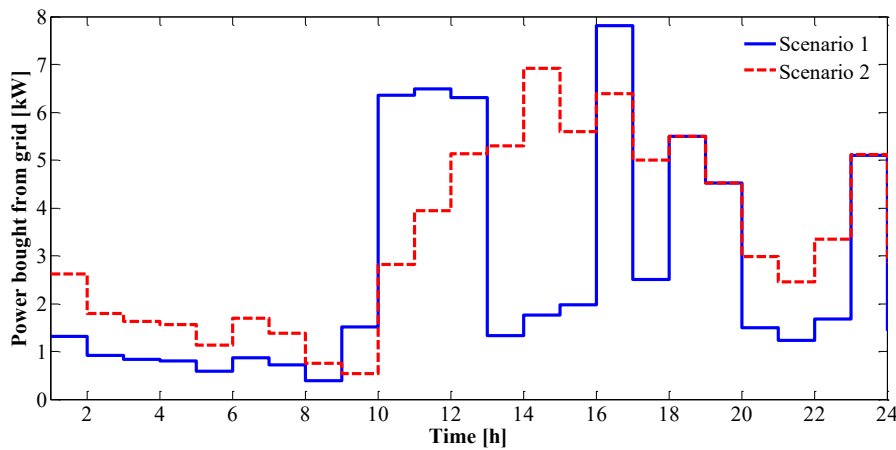


Fig. 6. Total power bought from the grid at each hour in two scenarios

Table 2. Energy cost and consumption in two scenarios

	Energy Cost [\$]	Energy Consumption [kWh]
Scenario 1	5.95	35.03
Scenario 2	7.66	52.53

three case studies can be summarized as follows:

- Case 1: No DR program for HVACs
- Case 2: No hourly and overall comfort level for consumers and a linear dissatisfaction function for consumers
- Case 3: Only thermostat setting limit for HVACs to model user comfort

The consumed HVAC power in the aforementioned three case studies is depicted in Fig. 7. As it can be seen, in case 2 and case 3, HVAC consumption is decreased too much due to not modeling user dissatisfaction properly. Moreover, the user's consumption pattern and habits are totally neglected when

user comfort model is not comprehensive. Therefore, both of these models are incomplete and unrealistic in practice and cannot be implemented in real cases.

To support the effectiveness of the method proposed in this study, it was tested on three additional smart homes. The results of HVAC consumption are shown in Fig. 8. It can be seen from this Figure that for all of these three houses, HVAC consumption power is decreased while the user behavior and consumption pattern is maintained. The results of consumed HVAC power and energy cost with and without HEMS are given in Table 3. The first house, which has an overall comfort

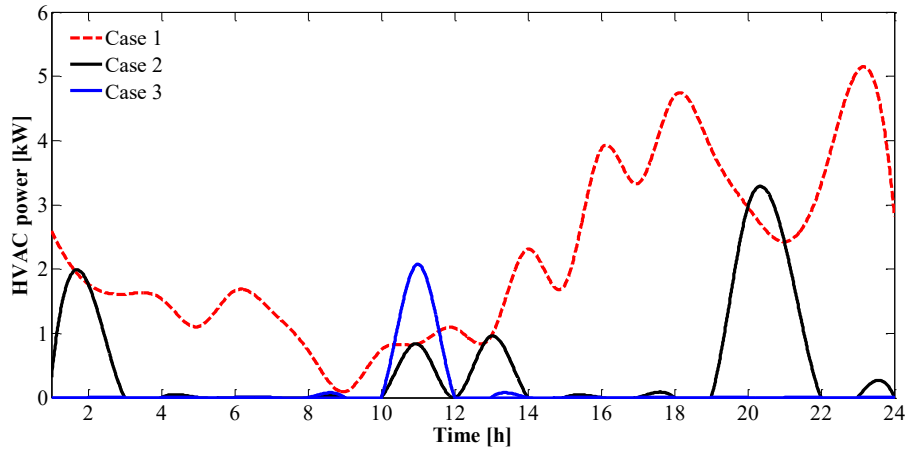


Fig. 7. Hourly HVAC energy consumption in three case studies

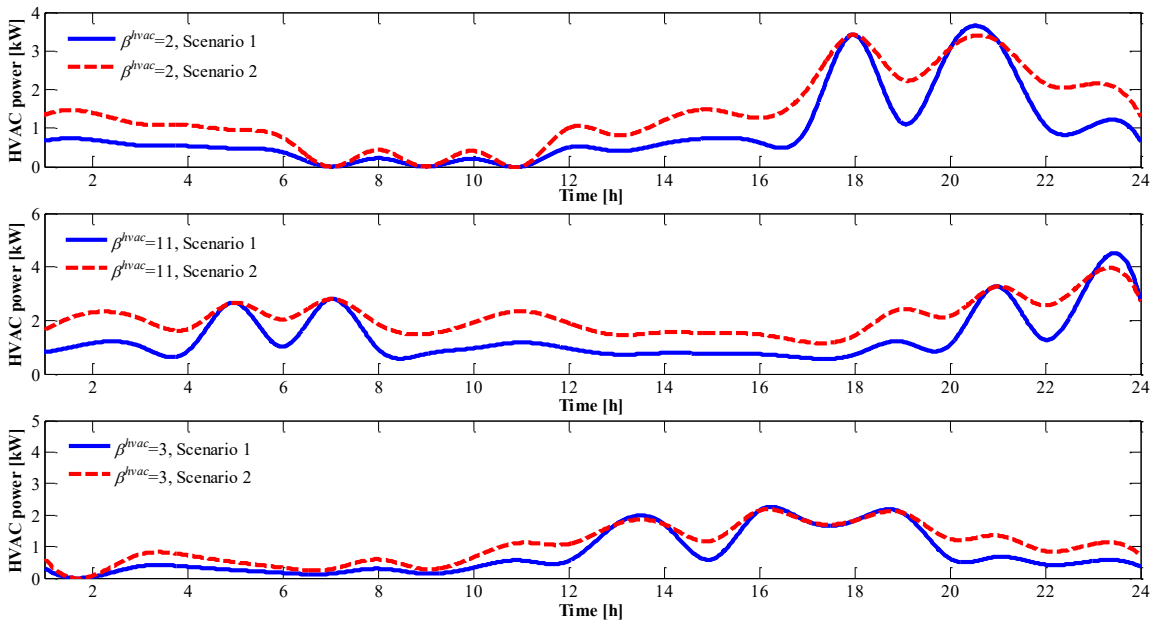


Fig. 8. Hourly HVAC energy consumption for three houses in two scenarios

Table 3. Energy cost and consumption for three houses in two scenarios

		Energy Cost [S]	Energy Consumption [kWh]
House 1 ($\beta^{hvac}=2$)	Scenario 1	2.66	21.27
	Scenario 2	3.77	32.84
House 2 ($\beta^{hvac}=11$)	Scenario 1	5.7	32.7
	Scenario 2	7.5	50.22
House 3 ($\beta^{hvac}=3$)	Scenario 1	2.05	18
	Scenario 2	2.69	24.74

level of 2, has maximum energy savings with 35.23% reduction in HVAC consumption and 29.44% decrease in energy costs.

5. CONCLUSION

In this paper, a HEMS structure for appliance scheduling of smart homes based on user behavior was designed. Machine learning tools were used to learn user's behavior regarding HVAC systems. Moreover, a shifting based DR was also proposed for the house. The designed structure was applied to a real case smart home located in Austin, Texas. Simulation results demonstrated that the current structure could successfully decrease energy cost and consumption by 22.3% and 33.3%, respectively without causing dissatisfaction to the user. Moreover, the current structure has the flexibility to adapt to various user behaviors and comfort levels. To confirm the effectiveness of this method, it was tested on three additional houses as well and the results showed an acceptable trend.

REFERENCES

- [1] H. Kikusato, K. Mori, S. Yoshizawa, Y. Fujimoto, H. Asano, Y. Hayashi, A. Kawashima, S. Inagaki, T. Suzuki, Electric Vehicle Charge–Discharge Management for Utilization of Photovoltaic by Coordination Between Home and Grid Energy Management Systems, *IEEE Transactions on Smart Grid*, 10(3) (2019) 3186-3197.
- [2] H. Shareef, M.S. Ahmed, A. Mohamed, E.A. Hassan, Review on Home Energy Management System Considering Demand Responses, Smart Technologies, and Intelligent Controllers, *IEEE Access*, 6 (2018) 24498-24509.
- [3] M. Yousefi, A. Hajizadeh, M.N. Soltani, A Comparison Study on Stochastic Modeling Methods for Home Energy Management Systems, *IEEE Transactions on Industrial Informatics*, 15(8) (2019) 4799-4808.
- [4] F. Luo, G. Ranzi, C. Wan, Z. Xu, Z.Y. Dong, A Multistage Home Energy Management System With Residential Photovoltaic Penetration, *IEEE Transactions on Industrial Informatics*, 15(1) (2019) 116-126.
- [5] G. Dong, Z. Chen, Data-Driven Energy Management in a Home Microgrid Based on Bayesian Optimal Algorithm, *IEEE Transactions on Industrial Informatics*, 15(2) (2019) 869-877.
- [6] B. Celik, R. Roche, D. Bouquain, A. Miraoui, Decentralized Neighborhood Energy Management With Coordinated Smart Home Energy Sharing, *IEEE Transactions on Smart Grid*, 9(6) (2018) 6387-6397.
- [7] H. Huang, Y. Cai, H. Xu, H. Yu, A Multiagent Minority-Game-Based Demand-Response Management of Smart Buildings Toward Peak Load Reduction, *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 36(4) (2017) 573-585.
- [8] T. Molla, B. Khan, B. Moges, H.H. Alhelou, R. Zamani, P. Siano, Integrated optimization of smart home appliances with cost-effective energy management system, *CSEE Journal of Power and Energy Systems*, 5(2) (2019) 249-258.
- [9] P. Zhao, H. Wu, C. Gu, I. Hernando-Gil, Optimal home energy management under hybrid photovoltaic-storage uncertainty: a distributionally robust chance-constrained approach, *IET Renewable Power Generation*, 13(11) (2019) 1911-1919.
- [10] K.M. Tsui, S.C. Chan, Demand Response Optimization for Smart Home Scheduling Under Real-Time Pricing, *IEEE Transactions on Smart Grid*, 3(4) (2012) 1812-1821.
- [11] S. Althaher, P. Mancarella, J. Mutale, Automated Demand Response From Home Energy Management System Under Dynamic Pricing and Power and Comfort Constraints, *IEEE Transactions on Smart Grid*, 6(4) (2015) 1874-1883.
- [12] S. Lee, B. Kwon, S. Lee, Joint Energy Management System of Electric Supply and Demand in Houses and Buildings, *IEEE Transactions on Power Systems*, 29(6) (2014) 2804-2812.
- [13] M. Shafie-Khah, P. Siano, A Stochastic Home Energy Management System Considering Satisfaction Cost and Response Fatigue, *IEEE Transactions on Industrial Informatics*, 14(2) (2018) 629-638.
- [14] A. Anvari-Moghaddam, H. Monsef, A. Rahimi-Kian, Optimal Smart Home Energy Management Considering Energy Saving and a Comfortable Lifestyle, *IEEE Transactions on Smart Grid*, 6(1) (2015) 324-332.
- [15] H.T. Nguyen, D.T. Nguyen, L.B. Le, Energy Management for Households With Solar Assisted Thermal Load Considering Renewable Energy and Price Uncertainty, *IEEE Transactions on Smart Grid*, 6(1) (2015) 301-314.
- [16] M. Pipattanasomporn, M. Kuzlu, S. Rahman, An Algorithm for Intelligent Home Energy Management and Demand Response Analysis, *IEEE Transactions on Smart Grid*, 3(4) (2012) 2166-2173.
- [17] P. Chavali, P. Yang, A. Nehorai, A Distributed Algorithm of Appliance Scheduling for Home Energy Management System, *IEEE Transactions on Smart Grid*, 5(1) (2014) 282-290.
- [18] A. Naeem, A. Shabbir, N.U. Hassan, C. Yuen, A. Ahmad, W. Tushar, Understanding Customer Behavior in Multi-Tier Demand Response Management Program, *IEEE Access*, 3 (2015) 2613-2625.
- [19] P. Samadi, H. Mohsenian-Rad, V.W.S. Wong, R. Schober, Tackling the Load Uncertainty Challenges for Energy Consumption Scheduling in Smart Grid, *IEEE Transactions on Smart Grid*, 4(2) (2013) 1007-1016.
- [20] X. Chen, T. Wei, S. Hu, Uncertainty-Aware Household Appliance Scheduling Considering Dynamic Electricity Pricing in Smart Home, *IEEE Transactions on Smart Grid*, 4(2) (2013) 932-941.
- [21] Z. Zhou, F. Zhao, J. Wang, Agent-Based Electricity Market Simulation With Demand Response From Commercial Buildings, *IEEE Transactions on Smart Grid*, 2(4) (2011) 580-588.
- [22] S. Li, D. Zhang, A.B. Roget, Z.O. Neill, Integrating Home Energy Simulation and Dynamic Electricity Price for Demand Response Study, *IEEE Transactions on Smart Grid*, 5(2) (2014) 779-788.
- [23] L. Yu, T. Jiang, Y. Zou, Online Energy Management for a Sustainable Smart Home With an HVAC Load and Random Occupancy, *IEEE Transactions on Smart Grid*, 10(2) (2019) 1646-1659.
- [24] D. Zhang, S. Li, M. Sun, Z. O'Neill, An Optimal and Learning-Based Demand Response and Home Energy Management System, *IEEE Transactions on Smart Grid*, 7(4) (2016) 1790-1801.
- [25] O. Longe, K. Ouahada, S. Rimer, H. Ferreira, A. J. Han Vinck, Distributed Optimisation Algorithm for Demand Side Management in a Grid-Connected Smart Microgrid, *Sustainability*, 9 (2017) 1088.
- [26] M. Carrion, J.M. Arroyo, A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem, *IEEE Transactions on Power Systems*, 21(3) (2006) 1371-1378.
- [27] Pecan Street Inc., <http://dataport.cloud/.com>, October 2015 - April 2018.

HOW TO CITE THIS ARTICLE

N. Gholizadeh, M. Abedi, H. Nafisi, M. Marzband, *Learning-Based Energy Management System for Scheduling of Appliances inside Smart Homes*, *AUT J. Elec. Eng.*, 51(2) (2019) 211-218.

DOI: [10.22060/ej.2019.16892.5296](https://doi.org/10.22060/ej.2019.16892.5296)

