2020 28th Iranian Conference on Electrical Engineering (ICEE)

Optimal Energy Scheduling Considering Consumers Preference in a Smart Home

Mohsen Bihamta Toosi
Department of Electrical Engineering
(Center of Excellence on Soft Computing and Intelligent Information Processing)
Ferdowsi University of Mashhad
Mashhad, Iran
mohsen.bihamta@mail.um.ac.ir

Habib Rajabi Mashhadi
Department of Electrical Engineering
(Center of Excellence on Soft Computing and Intelligent Information Processing)
Ferdowsi University of Mashhad
Mashhad, Iran
h_mashhadi@um.ac.ir

***Abstract*— Residential buildings are estimated to have a significant percentage of energy consumption in the world. Demand-side management (DSM) improves the grid stability by providing economic incentives with increasing flexibility in demand and reducing a peak to average ratio. The success of applications in DSM heavily depends on the welfare and satisfaction of consumers, or a significant reduction of the customers electricity bill. In this paper, the genetic algorithm is used to optimize the problem. Moreover, two scenarios are discussed. In the first one, occupants have announced their preferred time of household appliances usage. On this basis, the scheduled for the use of household appliances is optimally determined in order to minimize the cost of electricity usage in addition to meeting end-user preferences on when to use devices. In the second one, customers are offered a significant reduction in their electricity bill by changing the operation time of some of their household appliances. The proposed model is implemented for the hottest day of 2018 in New York City. The results demonstrate that the consumers preference is satisfied, and the peak load is declined down to the value, which is desirable for the utility. Besides, the model doesn't produce a new peak load when the power price is low. Hence the system stability is increased, which reflects the significant effectiveness of this model.**

Keywords — Demand-side management, smart home, consumers preference, appliance scheduling.

I. INTRODUCTION

The consumption of energy in buildings now comprising approximately 32% in a world wide scale. These buildings consume 65% of total electrical energy, along with causing 36% of air pollution due to the emission of Co2 [1]. Consuming energy in the residential sector is roughly 30% up to 40% in the world [2]. The highly growing urbanization, construction of buildings, and residential skyscrapers, all in company with growing utilization of cooling systems in these buildings require energy conservation strategy and optimal energy management. With exploiting useful energy patterns, the proper reduction of electrical energy consumption at the peak of electrical load can be achieved [3], [4].

Demand-side management (DSM) is the process of balancing the produced and consumed electrical power in a grid via controlling the load of the grid, however, not changing the amount of power generated from the grid. DSM indicates a change in the conventional manner of consumers electricity consumption in response to changing electricity prices or owing to incentives to clients. This yields reduction of the electricity bill through less power consumption, when power prices are high or the reliability of the system is in peril. There are several approaches, in which users engage in load management programs. DSM is generally divided into two categories founded on price-based and incentive-based programs, Refer to [5] for further studies.

Nowadays, smart homes are increased dramatically due to advancements in this field. Following [1], in these homes, convenient structures are designed for residents, lead to reduced energy costs as well as a high level of comfort. These smart houses have a bi-directional connection between utility and occupants, which is made by smart meter and advanced metering infrastructure. In this regard, the grid operator can provide the consumers time-dependent prices. (whether real-time or day-ahead). In such a condition, end-users can dynamically interact with the grid and receive price signals, and then, manage their power consumption according to these signals.

Even though the DSM is an appealing method for increasing flexibility in demand and reduction of peak load, but the satisfaction and welfare of consumers must be taken into account. For instance, in the United States of America in 2015, the peak reduction resulted from DSM programs was just 6.6 % [6]. Because electricity is an essential resource for consumers. For example, Centolla showed that for an hour of an electrical power outage, home occupants are willing to pay even up to 2.53 $/KWH, which is higher when compared to the actual electricity price [7]. This indicates that consumers tendency is not to sacrifice their welfare to lower costs.

In [8], a direct load control algorithm with load shedding has been proposed to apply a power shortage to a wide range of end-use consumers. In addition to the fact that the load disconnection cause customer dissatisfaction, the main drawback of this paper is that the electricity prices are constant throughout the day. Thus, the daily load curve is almost smooth and uniform. Althaher et al. [9] focused on minimizing the electricity bill and consumers dissatisfaction in the domestic sector by using an iterative algorithm. The main contribution of this paper is to target a certain amount of electricity bill, which can cause customers dissatisfaction. So, consumers are not encouraged enough to participate in DSM programs. In [10], the effect of customers behavior on DSM in South Africa has illustrated. This paper asserts that the peak load is reduced by 3.7 % if only the time of use tariff is employed. Nonetheless, the decrease in peak load is 5.7 % if it is associated with the house display units. The one in [5] has

978-1-7281-7296-5/20/$31.00 ©2020 IEEE

dealt with the challenges and disadvantages of DSM in China and identifies effective strategies to alleviate market problems. One of the main challenges in implementing these programs is how to determine price electricity. In [11], Macedo et al. examine the application of DSM programs in Brazil. Their aim is first to study the load profile and consumption curves, and thus the consumers classifier can be made according to this notion. In the following, load pattern curves are generated for consumers to choose their proper design while [12] Jindal et al. proposed a rational demand response for the home section, which is mainly based on consumer data analysis. The proposed scheme is offered at two levels. In the first level, the consumer load is reduced down to amount where the comfort of end-users is not violated. In the second level, the peak load is reduced. However, the users comfort may be violated. Also, the clients may not be willing to use these programs in comparison to reducing the shared electricity bill.

The success of applications in DSM heavily depends on the welfare and satisfaction of consumers, or a significant reduction of the shared electricity bill. In this paper, two scenarios are discussed. In the first one, occupants have announced their preferred time of household appliances usage. On this basis, the scheduled for the use of household appliances is optimally determined in order to minimize the cost of electricity usage in addition to meeting end-user preferences on when to use devices. In the second one, customers are offered a significant reduction in their shared electricity bill by changing the time of some of their household appliances. We presume that the day-ahead bid is received through the smart meter. Moreover, to attain automatic control, we used the ZigBee wireless network, which is a high-level communication protocol.

The remainder of this paper is arranged as follows. Part II, discusses the system model. In part III, the optimization methodology is expressed. In part IV, we describe the scheduling result. Finally, part V concludes the paper.

II. System Model

Since involving all appliances in DSM programs may limit users, which brings customer dissatisfaction, in this paper, occupants entertainment equipment is not considered. The devices which are considered for energy management, are responsible for about 70% of a home's electricity consumption. Hence, devices are divided into three categories.

A. Thermal Appliances

As shown in Figure 1, a significant value of household electricity consumption is related to heating ventilation and air conditioning (HVAC), and water heater. Therefore, load management in this section can significantly help reduce the amount of electricity bill. To ensure the thermal comfort of our occupants, we use a preferred interval as a constraint that shows in equations (3) and (5). The indoor temperature is determined as follows [13]:

$$T_{in}(i) = \alpha P_{HVAC}(i) + \beta (T_{out}(i) - T_{in}(i-1)) + T_{in}(i-1) \quad (1)$$

$$P_{HVAC}(i) \le P_{HVAC}^{\max} \quad (2)$$

$$T_{in}^{\min} \le T_{in}(i) \le T_{in}^{\max} \quad (3)$$

where α denotes the thermal characteristic of HVAC. Also, β is the work mode of HVAC in such way that $\beta > 0$ indicates

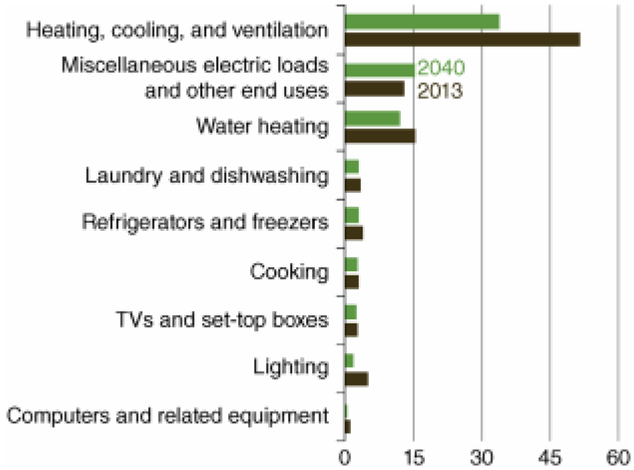

Fig. 1. Energy consumption in the residential sector, 2013 and 2040 (million Btu per household per year) [1]

heating, and $\beta < 0$ is for cooling mode. T_{in} is indoor temperature, and T_{out} corresponds to the outdoor temperature. P_{HVAC}^{max} is HVAC rated power. T_{in}^{max} and T_{in}^{min} are upper and lower bounds of consumer preferences of indoor temperature, respectively.

The temperature of hot water is determined as [14]:

$$T_{hw}(i+1) = \frac{T_{hw}(i).(V_{\tan k} - r_i.\Delta t) + T_{cw}.r_i.\Delta t}{V_{\tan k}} \quad (4)$$

$$+ \frac{1\,gal * \Delta t}{8.34\,lb * V_{\tan k} * 60\dfrac{\min}{h}} . \left[\frac{P_{wh} * 3412Btu}{KWh} + \frac{A_{\tan k}.(T_a - T_{ic})}{R_{\tan k}} \right]$$

$$T_{hw}^{\min} \le T_{hw}(i) \le T_{hw}^{\max} \quad (5)$$

$$P_{wh} \le P_{wh}^{\max} \quad (6)$$

where T_{hw} is the outlet water temperature in the hot water tank. V_{tank}, R_{tank} and A_{tank} are the overall volume, heat resistance, and area of the tank, respectively. r_i corresponds to the flow rate of the hot water in period i. T_{cw} implies incoming cold water temperature, and T_a corresponds to the room temperature. P_{wh}^{max} is a water heater rated power. T_{hw}^{max} and T_{hw}^{min} are upper and lower bounds of consumer preferences of hot water temperature**.** If the water heater remains switched-on at the next time slot, the hot water temperature will be attained from the (7), and if the water heater is switched off at the next time slot, the output water temperature will be obtained from the (8) [15].

$$T_{hw}(i+1) = \left(\frac{9}{5}\right) \left[\frac{(m_1 - m_2(i)) * c_{hw} * T_{hw}(i) + m_2(i) * c_{cw} * T_{cw}}{(m_1 - m_2(i)) * c_{hw} + m_2(i) * c_{cw}} \right]$$

$$+ \frac{P_{wh} * \Delta t}{2.42 * V_{\tan k}} + 32 \quad (7)$$

$$T_{hw}(i+1) = \left(\frac{9}{5}\right) \left[\frac{(m_1 - m_2(i)) * c_{hw} * T_{hw}(i) + m_2(i) * c_{cw} * T_{cw}}{(m_1 - m_2(i)) * c_{hw} + m_2(i) * c_{cw}} \right]$$

$$+32 \quad (8)$$

where c_{hw} and c_{cw} are heat capacity of the hot and cold water, respectively. m_1 indicates an overall mass of water in the tank, and m_2 overall mass of the hot water consumed at slot (i).

B. Schedulable Appliances

Schedulable appliances involved those that their beginning time can be altered among the day in reply to user preferences and electricity prices. For these appliances, to ensure their running time length, (9) needs to be considered.

$$\sum_{i=i_{start}}^{i_{end}} u_t(i) = N_s \tag{9}$$

where $u_t(i)$ is the operation state of schedulable appliances in which if $u_t(i)$ =1, the appliances are on, otherwise the appliances are off $u_t(i)$ =0. Moreover, N_s is the number of operation slots. Some appliances in this category, such as dishwasher or clothes dryer, cannot be stopped after being switched-on until at the end of their operation time. Accordingly, if (10) is realized, then (11) can be concluded.

$$u_d(i) = 1 \tag{10}$$

$$u_d(i+1) = u_d(i+2) = \ldots = u_d(i+N_s-1) = 1 \tag{11}$$

C. Electric Vehicle and Energy Storage System

The growing number of electric vehicles in use, in combination with storage devices, has the great potential to be used in DSM programs. To enhance battery life, the state of charge (SOC) all along with discharging and charging power ought to be constrained within a specific range as follows [16]:

$$P_{Dch,batt}(i) \le \left(\frac{P_{Dch,\max}}{\eta_{Dch}}\right).(1-u_{Batt}(i)) \tag{12}$$

$$P_{Ch,batt}(i) \le P_{ch,\max}.\eta_{ch}.u_{Batt}(i) \tag{13}$$

$$SOC_{\min} \le SOC(h) \le SOC_{\max} \tag{14}$$

where $P_{Dch,max}$ and $P_{ch,max}$ are the battery maximum discharging and charging powers, respectively. Furthermore, SOC_{max} and SOC_{min} are the upper and lower limits of the SOC of the battery, respectively. Also, η_{Dch} and η_{ch} are the overall battery's discharging and charging efficiencies, respectively, and $u_{Batt}(i)$ expresses status of the battery at hour h in a way that $u_{Batt}(i)$ = 0 discharging and $u_{Batt}(i)$ = 1 charging. E_{Batt} denotes the battery capacity. The state of charge is calculated as [16]:

$$SOC(h+1) = SOC(h) + \left(\frac{P_{ch,batt}(i) - P_{Dch,batt}(i).\Delta h_{setp}}{E_{batt}}\right) \tag{15}$$

III. Optimization Methodology

The Genetic Algorithm is a search heuristic based on the mechanism of natural selection and natural genetics. This algorithm is commonly used for optimization.

$$Min : \sum_{n=1}^{k} \mathrm{Cost}(n) + Discomfort(n) \tag{16}$$

$$\mathrm{Cost}(n) = P_{grid}(n).\,price(n).\,\Delta t \tag{17}$$

$$Discomfort(n) = \omega.t_p(n) + \gamma T_p(n) \tag{18}$$

where ω and γ are penalty coefficients for appliances delay operation time and the value of thermal comfort violation, respectively. Besides, t_p is the value of delay for using the appliances, and T_p is the degree of temperature violation.

The proposed algorithm is implemented in the single residence in hottest day of the year 2018 in New York City (07/01/2018). We apply a day-ahead scheme that demonstrated in Figure 2, and the outdoor temperature illustrated in figure 3.

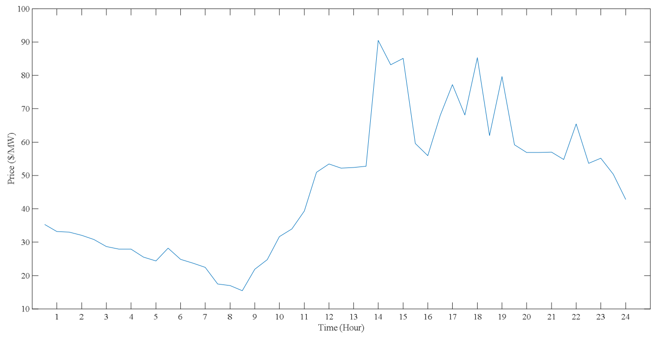

Fig. 2. Day-ahead price [17]

Each interval period is 30 minutes in this paper. Prediction of hot water consumption of a residential house is taken from [15].

IV. Scheduling Result

We have optimized our algorithm by employing MATLAB R2019b.

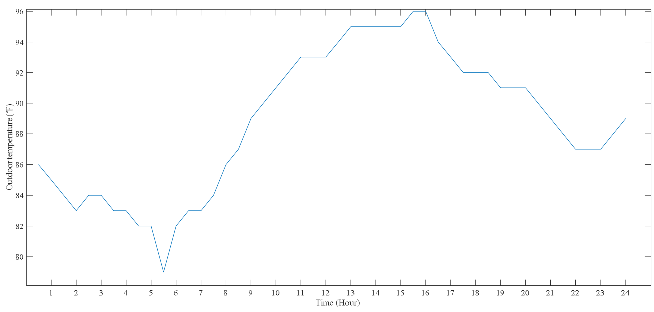

Fig. 3. Outdoor temperature [18]

A. The First Strategy

The best fitness of the population curve has been plotted, which is shown in Fig. 4. The consumer desires have received, in Tables I and II. Also, all the required parameters for devices are given in Table II. Electric cars are assumed to be in a house between 12 pm and 7 am. Also, batteries in the storage system can be charged or discharged at any hour of the day.

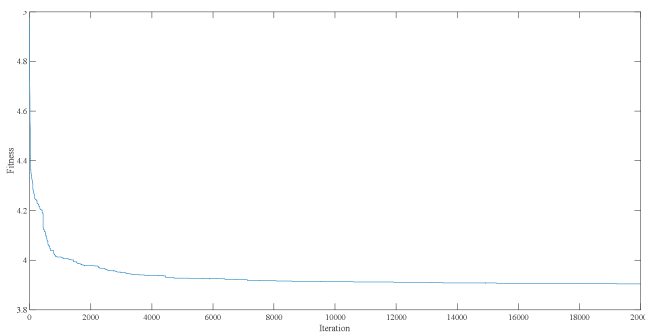

Fig. 4. Best fitness of the population

Table 1. Appliance parameters

Appliances	Min power (KW)	Max power (KW)	Prefer time	Run time (hour)
ventilation	0	2	00:00 – 24:00	24
Water heater	0	3	00:00 – 24:00	24
Dishwasher	1.4	1.4	8:00 – 14:00 or 17:30 – 22:00	2
Washing machine	2	2	8:30 – 19:00	2 (wash) 1 (dry)
Oven	2	2	9:00 – 14:30 & 17:00 – 22:30	2 2
Electric kettle	1	1	6:00 – 8:00	0.5
Vacuum cleaner	0.8	0.8	9:00 – 13:30 or 16:00 – 20:30	1

Table 2. Function parameters

Water heater parameters				HVAC parameters	
T_{cw}	65 °F	V_{tank}	200 Liter	α	0.9
T_a	76 °F	R_{tank}	20 m^2.°F/W	β	-10
T_{hw}^{min}	125 °F	A_{tank}	2 m^2	T_{in}^{min}	68 °F
T_{hw}^{max}	135 °F	c_{cw}	4.2 J/ °K	T_{in}^{max}	76 °F
$T_{in}(i\text{-}1)$, i=1	65 °F	c_{hw}	4.18 J/ °K	$T_{in}(i\text{-}1)$, i=1	72 °F
Electric vehicle parameters			**Storage system parameters**		
Maximum charging	4.5 (KWh)		Maximum charging	6.5 (KWh)	
Maximum discharging	-4.5 (KWh)		Maximum discharging	-6.5 (KWh)	
η_{ch}	0.92		η_{ch}	0.92	
η_{Dch}	0.92		η_{Dch}	0.92	

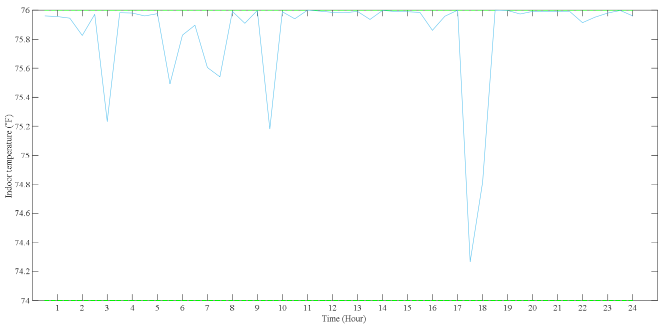

Fig. 5. Indoor temperature

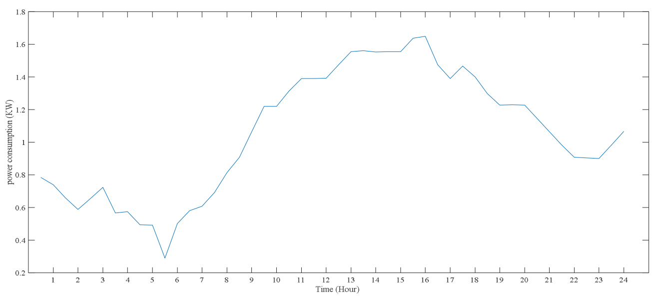

Fig. 6. HVAC power consumption

In this paper, the suitable temperature of the consumer was between 68 to 76. As shown in Fig. 3, the outdoor temperature in the coldest time of the day is 79, which is higher than the mentioned interval. Nevertheless, as displayed in Fig. 5, the indoor temperature stands exactly between 68 to 76. The power consumption of HVAC is demonstrated in Fig. 6.

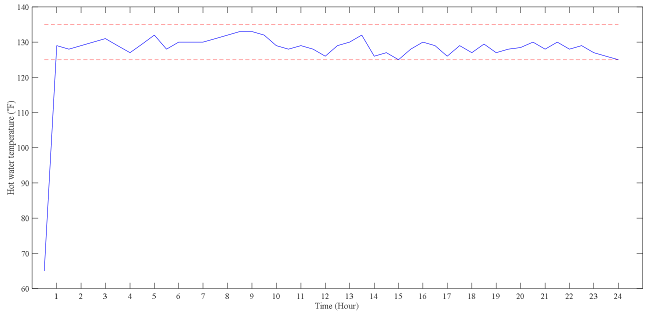

Fig. 7. Hot water temperature

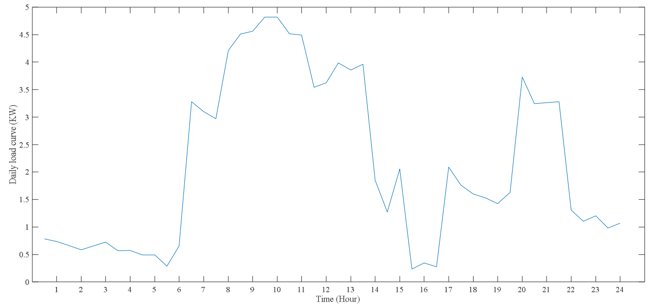

Fig. 8. Daily load curve in first strategy

As seen in Fig. 7, the hot water temperature is always between 125 °F to 135 °F, which this value meets the consumer desires. The daily load curve is illustrated in Fig. 8.

The operation time of appliances is given in Table III, as well. The curve of the electric vehicle charging state, the batteries storage charging/discharging states are also shown in Fig. 9. With due attention to Fig. 9, the batteries are charged under low grid tariffs, which are discharged when the price of electricity is high. Since all the consumer constraints are met, resultantly, the consumer enthusiastically participates in DSM programs.

Table 3. Operation time of appliances in first strategy

Appliances	Operation time	Appliances	Operation time
Oven	12:00- 14:00 &19:30-21:30	Vacuum cleaner	10:00 – 11:00
Washing machine	08:30- 11:30	Electric kettle	07:30- 08:00
Dishwasher	08:00 – 10:00		

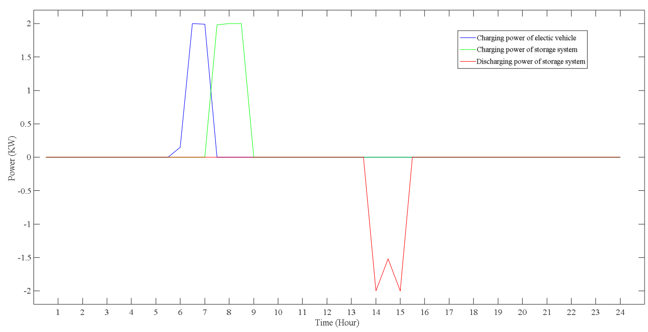

Fig. 9. Charging and discharging power of electric vehicle and storage system in first strategy

B. The Second Strategy

In this strategy, the time operation constraints of using schedulable appliances and electrical vehicle charging state are removed. The results are given in Table IV. The daily load curve is shown in Fig. 10, as well. The curve of the electrical vehicle charging state is demonstrated in Fig. 11. Regarding these results, the consumer, a small change in power consumption pattern, contributes to the 17% reduction of electricity bill in comparison to the previous strategy.

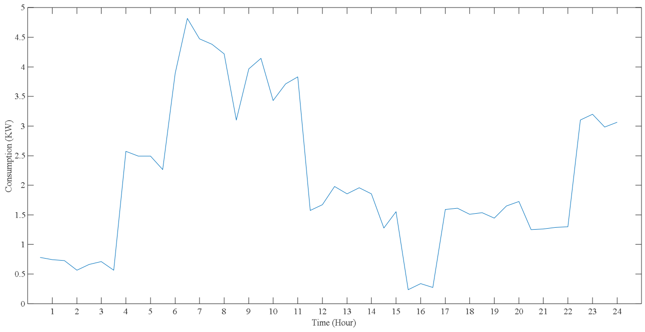

Fig. 10. Daily load curve in second strategy

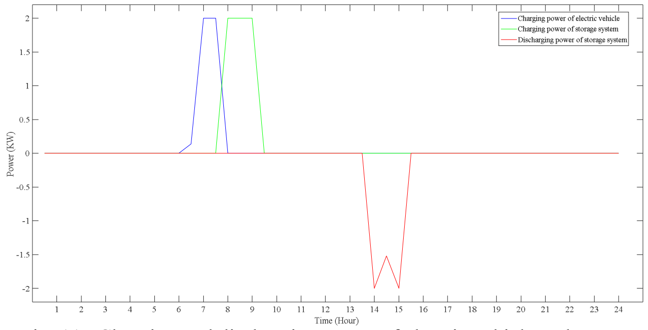

Fig. 11. Charging and discharging power of electric vehicle and storage system in second strategy

Table 4. Operation time of appliances in second strategy

Appliances	**Operation time**	**Appliances**	**Operation time**
Oven	09:30- 11:30 & 20:30- 22:30	Vacuum cleaner	09:00-10:00
Washing machine	04:00- 07:00	Electric kettle	07:30- 08:00
Dishwasher	06:00- 08:00		

V. CONCLUSION

In this paper, for daily load management of a consumer, two scenarios were illustrated and discussed. As it was evident in the first scenario, in addition to minimizing the electricity bill and limiting the peak load of grid, all of the consumers requirement was met. Also, in this scenario, all of appliances work at the stated time, and the temperature within limits was allowed. For better explanation, the customer preferences are fully satisfied in the worst case, which are much desirable. In the second scenario, it is also suggested to consumers that by changing the clock use of the washing machine and dishwashing and time of charging electric cars, a considerable amount of money on electricity bill would be saved. The results of both scenarios were determined that the model does not produce a new peak load when the power cost is low.

REFERENCES

[1] H. Gabbar, Energy conservation in residential, commercial, and industrial facilities. (John Wiley & Sons, Inc., Hoboken, New Jersey, 2018).

[2] H. T. Haider, O. H. See, and W. Elmenreich, “A review of residential demand response of smart grid,” Renew. Sustain. Energy Rev., vol. 59, pp. 166–178, 2016.

[3] P. Chavali, P. Yang, and A. Nehorai, “A distributed algorithm of appliance scheduling for home energy management system,” *IEEE Trans. Smart Grid,* vol. 5, no. 1, pp. 282–290, 2014.

[4] M. Eydi, S. Hosseini and R. Ghazi, "A New High Gain DC-DC Boost Converter with Continuous Input and Output Currents", 10th International Power Electronics, Drive Systems and Technologies Conference (PEDSTC), Shiraz, Iran, 2019.

[5] P. Guo, V. O. K. Li, and J. C. K. Lam, “Smart demand response in China: Challenges and drivers,” Energy Policy, vol. 107, no. March, pp. 1–10, 2017.

[6] J. R. Vázquez-Canteli and Z. Nagy, “Reinforcement learning for demand response: A review of algorithms and modeling techniques,” Appl. Energy, vol. 235, no. November 2018, pp. 1072–1089, 2019.

[7] K. T. Centolella P., Farber-DeAnda M., Greening L. A., “Estimates of the Value of Uninterrupted Service for The Mid-West Independent System Operator,” Harvard Electr. Policy Group, Harvard Kennedy Sch. Gov., pp. 1–49, 2010.

[8] H. Mortaji, S. H. Ow, M. Moghavvemi, and H. A. F. Almurib, “Load Shedding and Smart-Direct Load Control Using Internet of Things in Smart Grid Demand Response Management,” *IEEE Trans. Ind. Appl.*, vol. 53, no. 6, pp. 5155–5163, 2017.

[9] T. Hailu and J. A. Ferreira, “Piece-wise linear droop control for load sharing in low voltage DC distribution grid,” Proc. - 2017 IEEE South. Power Electron. Conf. SPEC 2017, vol. 2018-Janua, pp. 1–6, 2018.

[10] M. Begemann, G. A. Thopil, and M. Chudy, “Electricity load management potential based on the behaviour of consumers in the South African residential sector,” 2017 IEEE AFRICON Sci. Technol. Innov. Africa, AFRICON 2017, pp. 725–730, 2017.

[11] M. N. Q. Macedo, J. J. M. Galo, L. A. L. Almeida, and A. C. C. Lima, “Typification of load curves for DSM in Brazil for a smart grid environment,” Int. J. Electr. Power Energy Syst., vol. 67, pp. 216–221, 2015.

[12] A. Jindal, M. Singh, and N. Kumar, “Consumption-aware data analytical demand response scheme for peak load reduction in smart grid,” *IEEE Trans. Ind. Electron.*, vol. 65, no. 11, pp. 8993–9004, 2018.

[13] X. Hou, J. Wang, T. Huang, T. Wang, and P. Wang, “Smart Home Energy Management Optimization Method Considering Energy Storage and Electric Vehicle,” *IEEE Access*, vol. 7, pp. 144010–144020, 2019.

[14] S. Shao, M. Pipattanasomporn, and S. Rahman, “Development of physical-based demand response-enabled residential load models,” *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 607–614, 2013.

[15] K. Al-Jabery, D. C. Wunsch, J. Xiong, and Y. Shi, “A novel grid load management technique using electric water heaters and Q-learning,” 2014 IEEE Int. Conf. Smart Grid Commun. SmartGridComm 2014, pp. 776–781, 2015.

[16] A. Anvari-Moghaddam, H. Monsef, and A. Rahimi-Kian, “Optimal smart home energy management considering energy saving and a comfortable lifestyle,” *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 324–332, 2015.

[17] "Custom Reports - NYISO", Nyiso.com, 2018. [Online]. Available: https://www.nyiso.com/custom-reports?report=rt_lbmp_zonal.

[18] "New York City, NY Weather History | Weather Underground", Wunderground.com, 2020. [Online]. Available: https://www.wunderground.com/history/daily/us/ny/new-york-city/KLGA/date/2018-7-1.