Two-Stage Optimal Operation of Smart Homes Participating in Competitive Electricity Markets

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Abstract—End users have become active participants in local electricity market transactions because of the growth of the smart grid concept and energy storage systems (ESS). This participation is optimized in this article using a stochastic two-stage model considering the day-ahead and real-time electricity market data. This model optimally schedules the operation of a Smart Home (SH) to meet its energy demand. In addition, the uncertainty of wind and photovoltaic (PV) generation is considered along with different appliances. In this paper, the participation of an EV (electric vehicle), together with the battery energy storage systems, which allow for the increase in bidirectional energy transactions are considered. Demand Response (DR) programs are also incorporated which consider market prices in real-time and impact the scheduling process. A comparative analysis of the performance of a smart home participating in the electricity market is carried out to determine an optimal DR schedule for the smart homeowner. The results show that the SH's participation in a real-time pricing scheme not only reduces the operating costs but also leads to better than expected profits. Moreover, total, day-ahead and real-time expected profits are better in comparison with existing literature. The objective of this paper is to analyze the SH performance within the electrical market context so as to increase the system's flexibility whilst optimizing DR schedules that can mitigate the variability of end-users generation and load demand.

Index Terms—energy management system, energy storage system, demand response, internet of things, smart home, smart grid, stochastic programming

Nomenclature

Abbreviations

DR   Demand Response
EM   Electricity Market
EP   Expected Profit

ESS   Energy Storage System
EV   Electric Vehicle
IoT   Internet of Things
LM   Local Market
MILP   Mixed Integer Linear Programming
MW   Megawatt
PV   Photovoltaic
RTP   Real Time Pricing
SG   Smart Grid
SH   Smart Home

Indexes

t Time Index
ω Scenario Index
ξ EV mobility scenario Index

Variables

$P_t^{net,da}$ Day-ahead transacted energy
$P_{t\omega\xi}^{sold,rt}$ Energy sold from the home to the market
$P_{t\omega\xi}^{pur,rt}$ Energy purchased by the home from the market
$S_{t\omega\xi}$ Total spilled power of renewable sources
$L_{t\omega\xi}^{shed,sh}$ Space Heater load shedding
$L_{t\omega\xi}^{shed,swh}$ Electric Water Heater load shedding
$P_t^{wind,da}$ Day-ahead wind power generation
$P_t^{pv,da}$ Day-ahead PV generation
$P_t^{b,dis,da}$ Discharging power of battery in day-ahead
$P_t^{ev,dis,da}$ Discharging power of EV in day-ahead
$P_t^{b,ch,da}$ Charging power of battery in day-ahead
$P_t^{ev,ch,da}$ Charging power of EV in day-ahead
$P_{t\omega\xi}^{wind,rt}$ Real-time wind power generation
$P_{t\omega\xi}^{pv,rt}$ Real-time PV generation
$P_{t\omega\xi}^{b,dis,rt}$ Real-time discharged power of the battery
$P_{t\omega\xi}^{ev,dis,rt}$ Real-time discharged power of the EV
$P_{t\omega\xi}^{b,ch,rt}$ Real-time charged power of the battery

$P_{t\omega\xi}^{ev,ch,rt}$	Charging power of EV in real-time
$L_{t\omega\xi}^{sh,rt}$	Space Heater load in real-time
$L_{t\omega\xi}^{swh,rt}$	Electric water heater load in real-time
$L_{t\omega\xi}^{mrs,rt}$	Load of must-run services in real-time

Parameters

λ_t^{da}	Day-ahead electricity price
$\lambda_t^{sold,rt}$	Electricity price of the real-time sold energy
$\lambda_t^{pur,rt}$	Electricity price of the real-time purchased energy
π_ω	Probability of scenarios
π_ξ	Probability of scenarios for EV's mobility
V^S	Spillage cost
$VOLL^{sh}$	Value of lost load of the space heater
$VOLL^{swh}$	Value of lost load of the storage water heater

I. INTRODUCTION

A. Motivation

Smart home consumers' behaviour is rapidly becoming an emerging and important field of study recently. The objective is to optimize the scheduling of power consumption and increase energy efficiency thus reducing the cost of energy borne by the consumers. The introduction of competitive Electricity Markets (EM) has been combined with the concept of Smart Grids (SG). This combination means that clients are now capable of buying electricity from the grid according to their needs and preferences. The SH may also have sources of generation from local renewable energy sources which can improve the environmental, economic and reliability of energy within the SG. Therefore, it is important to create a model to better balance demand with the supply of energy.

With the increasing usage of renewable energies, such as Photovoltaic (PV) panels and wind micro-turbines, smart homes can also produce their energy to use, store or sell to the grid, making the client a producer beyond being a consumer. Therefore, clients can play an important role in the local market. It has been shown that the development of smart devices, HEMSs, energy storage systems (battery systems) and Electric Vehicles (EVs), allow consumers to make decisions concerning demand-side management. Another relevant aspect for the development of EVs and integration of renewable sources is actions taken by governments to reduce the carbon intensity of the energy system. These actions can include incentives provided for installing renewable energy sources and reduced costs for electric car charging stations. There has been a concurrent rise in digital devices, such as sensors, actuators, smartphones and smart appliances which increase the potential of the so-called Internet of Things (IoT). This means that it is possible to connect multitudes of devices and create communications between them through the Internet [1]. Through advanced automation systems, residential customers have access to complete supervision and control of the house equipment. This leads to increased complexity concerning SH modules requiring them to have integrated forecasting abilities, decision-making algorithms, wireless networking interfaces, amongst other features [2]. Any device connected to the grid can be controlled by the user.

Some applications already developed are associated with lighting, home security, thermostat regulation, medical treatment and data processing. With the development of new sensing technologies, communication tools, IoT concepts and management optimization software, smart homes proved to be a profitable case study to be invested in. Many studies have already shown multiple benefits of SH to both suppliers and costumers [3][4]. A SH can improve a consumer lifestyle in various ways. As already mentioned, SHs aim to reduce energy costs and consumption, but also facilitates users' lifestyles, providing comfort and quality of life. Furthermore, healthcare for individuals [5] and accurate market prices information can be provided [6]. Also, there is a need to optimize house energy consumption to minimize costs and reduce gas emissions. Despite the countless benefits associated with renewable energies, this type of energy production comes with a series of problems and challenges when it comes to its integration in the Local Market (LM). The biggest challenges are related to system management are regarding wind and solar power and its stochastic and unpredictable nature. Consumers' behaviour is also unpredictable and studying each type of consumer can help schedule and optimize the system [7]. One aspect helping solve these challenges is increasing the flexibility of the system, which can be achieved by the active participation of the consumers through DR programs. It is then in the sense of improving the performance of an SH system that this paper seeks to work on, by increasing flexibility and modelling a system to decrease energy costs all the while ensuring optimal consumer comfort. The increase of renewable energies integration and the possibility of modelling the demand side management allows for a reduction in electricity tariffs. However to deal with uncertainty it is necessary to utilize new and innovative methods which allow the model to optimize different conflicting objectives, operation costs and environmental restrictions [8].

B. Literature review

A significant number of studies in the literature have evaluated the performance of a SH on the electrical grids from different perspectives. In [9], a two-stage stochastic model for optimal management of domestic energy use is created. The first stage handles the aspects related to the day-ahead transactions between a home energy management system (HEMS) and a local market. While in the second stage, the real-time energy transactions problem with both energy management system and local market is modelled, accounting for both wind power generation and EV mobility uncertainty. The problem of scheduling of different SH appliances' operation is also formulated in [10], where a solution to minimize electricity cost and the maximum peak-load is proposed. Using the Mixed Integer Linear Programming (MILP) technique and a schedule was developed for a given a load demand profile, SH appliances, such as dishwasher, clothes washer and dryer, refrigerator, air-conditioner, oven and EV.

New specific control strategies and optimized models for managing energy service of HEMSs were increasingly developed recently, as many home appliances induce variations in power consumption during their working cycle. For instance, different control approaches to optimize energy flow management in a smart home were studied in [11]. A mixed-integer linear programming (MILP) approach was designed to solve the optimization problem between binary variables for representing the ON/OFF status of critical loads or continuous variables, mainly used to model energy storage systems. Generally, MILP is efficient in terms of the objective function (minimizing total energy cost for the consumer view), however, it requires higher computational time compared to other control approaches, due to the large number of variables and constraints in the system model. The problem of scheduling of different SH appliances' operation is also formulated in [10], where a solution to minimize electricity cost and the maximum peak-load is proposed. Based on the MILP technique and given a load demand profile, SH appliances, such as dishwasher, clothes washer and dryer, refrigerator, air-conditioner, oven and EV, were scheduled for minimizing cost. It was proven the effectiveness of the proposed solution regarding the objective functions. Furthermore, a PV panel was added to the model and it showed that also provided profit to the consumer, lowering electricity bills by using energy from the PV or selling it to the grid.

In [12], an optimal HEMS considering appliance operational dependencies is proposed. It considers both real-time pricing and demand charge tariff, and each appliance operational constraint is defined taking into concern the consumer's lifestyle. Recently demand charge tariffs have become popular which are defined as a one-off tariff based on the maximum demand recorded during a month. Therefore, this paper shows that this tariff creates an extra impact on the HEMS and it should be considered in this type of system. Numerical studies also illustrate that appliance operational management is relevant to secure better user-oriented HEMSs. In addition to providing a high level of comfort to consumers, residential energy management systems should handle the practical difficulties due to the uncertainty and technical limits. To this end, a two-stage model considering the uncertainties of residential load and small-scale renewable energy generation is proposed in [13], with the purpose of day-ahead and real-time energy management and regulation. Based on forecasted values of uncertain parameters, the authors achieved an optimal scheduling solution for the day-ahead stage. An adaptive neuro-fuzzy inference system is used on the real-time stage to regulate errors between real values and forecasted ones.

The proposed model showed that, for real-time management, the algorithm can optimize the control of the output power of the battery and controllable loads in comparison with ideal results. However, the model does not have total success and requires special strategies to improve its rate. Another control strategy for HEMSs is used in [14], which is a stochastic model predictive control strategy designed for a smart residential building. The model aims for the reduction of electricity cost and EV's battery degradation cost and the predictive HEMS ensures that all constraints regarding PV system, EV system, consumer's comfort and load demand. The results of the model system proposed showed that the system managed to reduce electricity costs.

As already described, various studies are concerned with energy management systems and optimization algorithms for energy cost and peak-load reduction. However, none of the papers provides a relevant study on the utilization of electricity bought from the LM and the electricity sold back to the grid. In [15], a new structure with small-scale renewable energy sources and energy storage systems where is taken into account the use of grid's electricity and the electricity selling is proposed. Particle swarm optimization is used to optimize mathematical formulas for energy cost and peak ratio. In comparison to previous work on this topic, the HEMS developed by the authors achieved the goal of energy cost reduction. Still, it is important to comment that in this paper user comforts, such as thermal comfort and consecutive tasks, are not considered within the problem's constraints.

II. METHODOLOGY

The model's performance was evaluated through a preliminary case study, taking into account a casual behaviour of a SH consumer using smart appliances. The model outputs are the hourly consumption, electricity bill and battery charge and discharge. The test system that is used to assess the proposed energy management system is taken from [9], [16] and [17]. However, both PV and wind power generation are used, and must-run services are specified as smart appliances, as it is shown in figure 1.

The smart home is considered to be relatively well lit and so the lighting system was modelled to consume energy mostly during the night (8:00 PM - 05:00 AM). Also, a 10W LED light power consumption per hour is considered. Furthermore, the washing machine consumption is assumed to be equal to 1.850 kW per cycle, based on the equipment's electrical connection rating. The dishwasher is considered to have an energy consumption of 1.5 kW per cycle. For a matter of simplicity, both the washing and dishwasher machines' operational cycles are assumed to equal to 1 hour, however, both machines have different daily schedules. Additionally, the price scheme used in the model is a real-time price (RTP), table I states it in $/kWh for a period of 24h. For a matter of comparison analysis, flat rate price is stated as 0.2384 $/kWh. The proposed model used the General Algebraic Modeling System (GAMS) for development and implementation [18].

A. Optimization Model

The developed model's objective function is to maximize the Expected Profit (EP) obtained by HEMS operating in the day-ahead and real-time local markets, and it is presented in equation 1 [9]. This system is capable of buying from or selling energy to the LM.
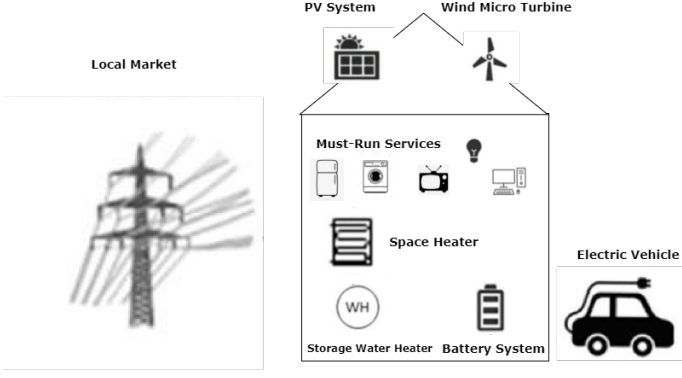
Fig. 1. Home energy management system (Modified from [9] and [17])

Time (h)	Real-time price ($/kWh)
1	0.17
2	0.18
3	0.19
4	0.22
5	0.23
6	0.24
7	0.24
8	0.23
9	0.31
10	0.28
11	0.27
12	0.26
13	0.24
14	0.23
15	0.25
16	0.25
17	0.26
18	0.31
19	0.27
20	0.26
21	0.23
22	0.21
23	0.21
24	0.19

$$Maximize\ EP = \sum_t \lambda_t^{da} P_t^{net,da} +$$
$$+ \sum_\omega \pi_\omega \sum_\xi \pi_\xi \sum_t [\lambda_t^{sold,rt} P_{t\omega\xi}^{sold,rt} - \lambda_t^{pur,rt} P_{t\omega\xi}^{pur,rt} - \quad (1)$$
$$-V^S S_{t\omega\xi} - VOLL^{sh} L_{t\omega\xi}^{shed,sh} - VOLL^{swh} L_{t\omega\xi}^{shed,swh}]$$

The first element presents the EP derived from energy trading in the day-ahead LM, due to the day-ahead price tariff (λ_t^{da}) and the day-ahead transacted energy ($P_t^{net,da}$), which is a profit when the home sells energy, and a cost when the home buys energy. The day-ahead stage constraints do not consider wind power and PV generation uncertainty. Equation 2 displays the power balance equation for the day-ahead schedule, depending on generation from wind micro-turbine ($P_t^{wind,da}$), PV system generation, battery charging or discharging power ($P_t^{b,dis,da}$ and $P_t^{b,ch,da}$, respectively), the

EV charging and discharging power ($P_t^{ev,dis,da}$ and $P_t^{ev,ch,da}$, respectively), the energy transacted with the LM ($P_t^{net,da}$) and the point forecasting of loads ($L_t^{sh,pred,da} + L_t^{swh,pred,da} + L_t^{mrs,pred,da}$).

$$P_t^{wind,da} + P_t^{pv,da} + \gamma_b P_t^{b,dis,da} + \gamma_{ev} P_t^{ev,dis,da} =$$
$$= L_t^{sh,pred,da} + L_t^{swh,pred,da} + L_t^{mrs,pred,da} + \quad (2)$$
$$+\gamma_b P_t^{b,ch,da} + \gamma_{ev} P_t^{ev,ch,da} + P_t^{net,da}$$

The uncertainty of the generation from wind power and EV mobility is included in the real-time stage through the use of stochastic scenarios. Also, a SH can both purchase and sell energy in real-time. Taking that into account, equation 3 displays the real-time power balance equation, where each parameter is described as it follows:

- Generation from the micro wind turbine ($P_t^{wind,rt}$);
- Generation from the PV system ($P_t^{pv,rt}$);
- Discharged and charged power of the battery ($P_t^{b,dis,rt}$ and $P_t^{b,ch,rt}$, respectively);
- EV Charging and discharging power ($P_t^{ev,dis,rt}$ and $P_t^{ev,ch,rt}$, respectively);
- Energy transacted with the LM ($P_t^{net,da}$);
- Point forecasting of loads ($L_{t\omega\xi}^{sh,rt} + L_{t\omega\xi}^{swh,rt} + L_{t\omega\xi}^{mrs,rt}$);
- Load shedding constraints, related to the lost energy of loads, such as the space heater and the storage water heater ($L_{t\omega\xi}^{sh,shed,rt} + L_{t\omega\xi}^{swh,shed,rt}$).

$$P_{t\omega\xi}^{wind,rt} + P_{t\omega\xi}^{pv,rt} + P_{t\omega\xi}^{b,dis,rt} + P_{t\omega\xi}^{ev,dis,rt} + P_{t\omega\xi}^{pur,rt} =$$
$$= L_{t\omega\xi}^{sh,rt} + L_{t\omega\xi}^{swh,rt} + L_{t\omega\xi}^{mrs,rt} - (L_{t\omega\xi}^{sh,shed,rt} + L_{t\omega\xi}^{swh,shed,rt}) +$$
$$+ P_{t\omega\xi}^{b,ch,rt} + P_{t\omega\xi}^{ev,ch,rt} + P_t^{net,da} + P_{t\omega\xi}^{sold,rt} \quad (3)$$

Within the day-ahead stage, it is noticeable that only one variable is used to detail traded energy between the SH and the LM, $P_t^{net,da}$. Furthermore, in this stage, $P_{t\omega\xi}^{pur,rt}$ and $P_{t\omega\xi}^{sold,rt}$ represent the purchased and sold energy, respectively, as the buying and selling prices may vary in real-time. In light of this, equation 4 states the line limitation of the power distribution network. This takes into account the energy purchased or sold from or to the grid in the real-time and day-ahead stages, which helps to simultaneously solve the day-ahead and real-time problems. Also, energy purchased and sold by the SH must be a positive value.

$$-f_{max} \leq P_t^{net,da} + P_{t\omega\xi}^{sold,rt} - P_{t\omega\xi}^{pur,rt} \leq f_{max} \quad (4)$$

III. DISCUSSION AND RESULTS

This section contains information related to the the performance of the proposed model and a comparative analysis within the project outputs and results of previous work is shown. The model assumes that a SH iss able to buy or sell electricity from the LM, store energy using ESS and produce electricity using small-scale renewable energy. Furthermore, PV and wind systems are integrated into the home energy

management problem as renewable sources of electricity. Additionally, an EV and a battery system are considered as ESSs and there are smart appliances integrated into the problem, including the space heater, electric water heater, washing and dishwasher machines and other small-scale load appliances. It should be noted that multiple charging and discharging of the EV and ESS may have negative impacts on their lifetime. Figure 2 shows the traded energy with the LM during the day-ahead stage. In figure 3, the energy sold and purchased in real-time are shown.
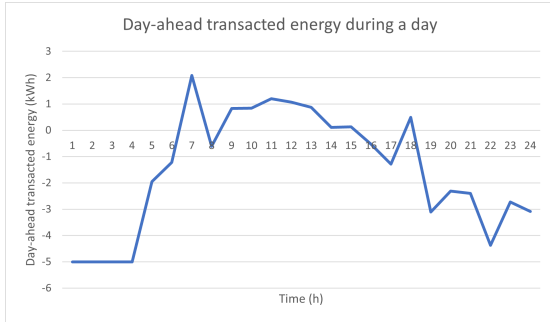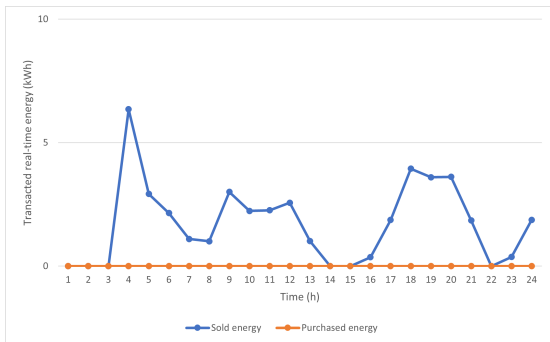

Fig. 2.   Traded energy in the Day-ahead stage

Fig. 3.   Traded energy in the Real-time stage

In figures 4 and 5, the charging and discharging of the battery are shown. It is noticable that the battery helps the HEMS at time, $t = 9$, $t = 10$ and $t = 18$, which constitute the system peak-load periods.
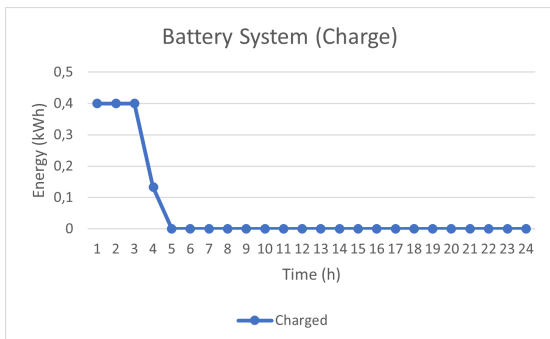

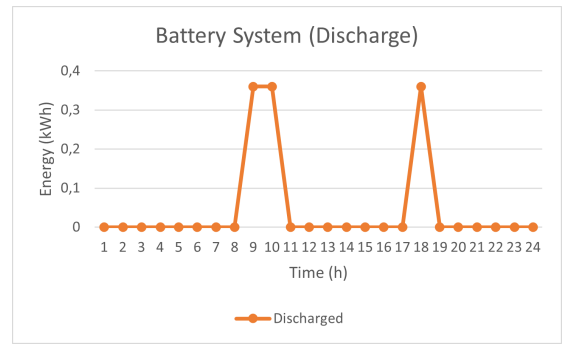Fig. 4.   Battery charging energy which is traded with the SH

Fig. 5.   Battery discharging energy which is traded with the SH

Charging od the EV occurs in periods 2 and 3 as it is required to be fully charged by 7 AM. Figures 6 and 7 represent the charging and discharging energy from the EV, which is traded with the DEMS excluding the discharged energy caused by EV's.
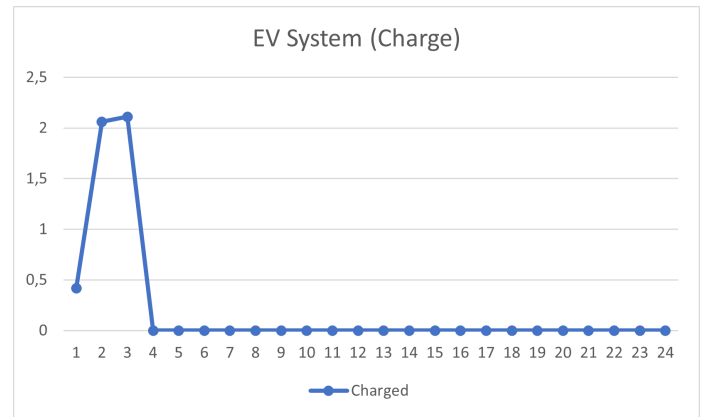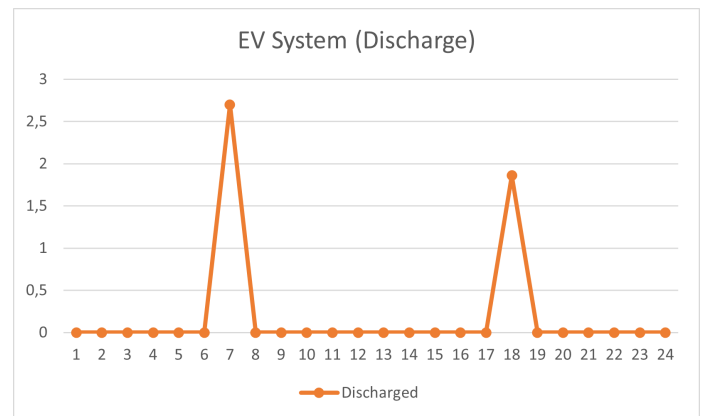

Fig. 6.   EV charging energy which is traded with the SH

Fig. 7.   EV discharging energy which is traded with the SH

The expected profits for the total, day-ahead and real-time stages of the stochastic HEMS problem using the real-time price is shown in Table II. Table II there is a negative day-ahead EP. This is because the SH consumes more energy that it produces, therefore, it buys more electricity than it sells. This is reversed in the real-time stage as the SH produces more electricity than it consumes so it has a positive EP.

IV. CONCLUSION

This paper has described a two-stage stochastic HEMS has been modelled using the MILP technique. The system can trade energy with the day-ahead and real-time LMs. Furthermore, PV and wind systems are integrated into the home energy management problem as renewable sources of electricity. The first stage modeled the day-ahead home energy management problem while the second stage considered the real-time problem, which also considered uncertainty related to wind power. The energy costs of the SH were reduced through careful scheduling of the loads. The model's performance was tested using the hourly energy consumption of a SH, end-users electricity bill and battery's charge and discharge rate. The simulation results reveal that the SH alternates between a consumer and a producer depending on the time period. Considering the Day-ahead market, the SH was expected to consume more electricity than it would generate resulting in a negative profit. This was reversed in the real-time stage where the SH exported energy thus deriving a profit from its transactions with the LM. Moreover, total, day-ahead and real-time expected profits are better in comparison with results obtained from previous works.

The model can be extended to integrate several smart homes or smart buildings as one system. As the number of consumers increases, there is an increase in the number of constraints and, in turn, the MILP technique loses efficiency when solving the energy management problem. In this sense, heuristic and metaheuristic approaches for this problem to reduce search space and better find the optimal solution, providing a more reliable model can be studied. Furthermore, HEMSs with more smart appliances integrated into the model can be studied to provide better distribution and total management of energy usage.

REFERENCES

[1] S. Talari, M. Shafie-khah, P. Siano, V. Loia, A. Tommasetti, and J. P. S. Catalão, "A review of smart cities based on the internet of things concept," *Energies*, vol. 10, no. 4, 2017. [Online]. Available: https://www.mdpi.com/1996-1073/10/4/421

[2] D. Y. Raghavendra Nagesh, J. V. Vamshi Krishna, and S. S. Tulasiram, "A real-time architecture for smart energy management," in *2010 Innovative Smart Grid Technologies (ISGT)*, 2010, pp. 1–4.

[3] M. Amer, A. Naaman, N. K. M'Sirdi, and A. M. El-Zonkoly, "Smart home energy management systems survey," in *International Conference on Renewable Energies for Developing Countries 2014*, 2014, pp. 167–173.

[4] M. Kasmi, F. Bahloul, and H. Tkitek, "Smart home based on internet of things and cloud computing," in *2016 7th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT)*, 2016, pp. 82–86.

[5] K. Deeba and R. K. Saravanaguru, "Context-aware healthcare system based on iot - smart home caregivers system (shcs)," in *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2018, pp. 1204–1208.

[6] S. Singh and J. Østergaard, "Use of demand response in electricity markets: An overview and key issues," in *2010 7th International Conference on the European Energy Market*, 2010, pp. 1–6.

[7] G. J. Osório, M. Shafie-khah, G. C. R. Carvalho, and J. P. S. Catalão, "Analysis application of controllable load appliances management in a smart home," *Energies*, vol. 12, no. 19, 2019.

[8] U. Zafar, S. Bayhan, and A. Sanfilippo, "Home energy management system concepts, configurations, and technologies for the smart grid," *IEEE Access*, vol. 8, pp. 119 271–119 286, 2020.

[9] A. S. Gazafroudi, M. Shafie-khah, E. Heydarian-Forushani, A. Hajizadeh, A. Heidari, J. M. Corchado, and J. P. Catalão, "Two-stage stochastic model for the price-based domestic energy management problem," *International Journal of Electrical Power Energy Systems*, vol. 112, pp. 404–416, 2019.

[10] F. A. Qayyum, M. Naeem, A. S. Khwaja, A. Anpalagan, L. Guan, and B. Venkatesh, "Appliance scheduling optimization in smart home networks," *IEEE Access*, vol. 3, pp. 2176–2190, 2015.

[11] Z. Wu, X.-P. Zhang, J. Brandt, S.-Y. Zhou, and J.-N. LI, "Three control approaches for optimized energy flow with home energy management system," *IEEE Power and Energy Technology Systems Journal*, vol. 2, no. 1, pp. 21–31, 2015.

[12] F. Luo, W. Kong, G. Ranzi, and Z. Y. Dong, "Optimal home energy management system with demand charge tariff and appliance operational dependencies," *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 4–14, 2020.

[13] V. Hosseinnezhad, M. Shafie-Khah, P. Siano, and J. P. S. Catalão, "An optimal home energy management paradigm with an adaptive neuro-fuzzy regulation," *IEEE Access*, vol. 8, pp. 19 614–19 628, 2020.

[14] M. Yousefi, A. Hajizadeh, M. N. Soltani, and B. Hredzak, "Predictive home energy management system with photovoltaic array, heat pump, and plug-in electric vehicle," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 1, pp. 430–440, 2021.

[15] H. T. Dinh, J. Yun, D. M. Kim, K.-H. Lee, and D. Kim, "A home energy management system with renewable energy and energy storage utilizing main grid and electricity selling," *IEEE Access*, vol. 8, pp. 49 436–49 450, 2020.

[16] A. S. Gazafroudi, T. Pinto, F. Prieto-Castrillo, J. Prieto, J. M. Corchado, A. Jozi, Z. Vale, and G. K. Venayagamoorthy, "Organization-based multi-agent structure of the smart home electricity system," in *2017 IEEE Congress on Evolutionary Computation (CEC)*, 2017, pp. 1327–1334.

[17] A. S. Gazafroudi, F. Prieto-Castrillo, and J. M. Corchado, "Residential energy management using a novel interval optimization method," in *2017 4th International Conference on Control, Decision and Information Technologies (CoDIT)*, 2017, pp. 0196–0201.

[18] GAMS, "User's guide," last accessed 15 June 2021. [Online]. Available: https://www.gams.com/latest/docs/UG_MAIN.html