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Towards Reducing Electricity Costs in an Energy Community Equipped with Home Energy Management Systems and a Local Energy Controller

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***Abstract*—An energy community equipped with Home Energy Management Systems (HEMSs) is considered in this paper. A local energy controller in the energy community makes it possible to transact energy between houses to support the different consumption patterns of each end-user. Price-based voluntary Demand Response (DR) programs are applied to each house to motivate end-users to alter their consumption patterns, allowing the necessary flexibility of the electrical grid. Also, the existence of Renewable Energy Sources (RES) micro-generation and an Energy Storage System (ESS) are taken into account. The results demonstrate that the proposed model based on Mixed-Integer Linear Programming (MILP) is fully capable of reducing daily electricity costs while considering end-users' comfort and respecting the different technical constraints.**

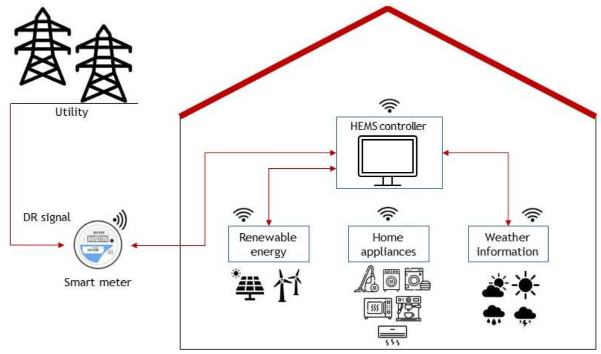

Fig. 1. Architecture of a HEMS with DR signal (adapted from [4]).

I. Introduction

The combination of Renewable Energy Sources (RES), Energy Storage Systems (ESS), Electric Vehicles (EV), and the evolution in automated devices such as sensors, actuators, smart metering, and Internet of Things (IoT) concepts made possible the introduction of the concept of Smart Home (SH) [1]. Through these various systems, the residents can access information about the status of the house and the possibility to control its equipment. Although this improves customer comfort, security, and energy consumption optimization, it also requires complex modules, advanced decision-making algorithms, and usually big initial investments [2].

The development of an SH should also integrate Demand Response (DR) programs as a way of encouraging the consumer to change his energy utilization habits to consume in low-price hours and, this way, overcome peak demand periods and become a more active participant in the energy local market. Modern SH aims to minimize energy costs and customer discomfort using a Home Energy Management System (HEMS), Fig. 1, which is responsible for coordinating and predicting all the different technologies' outputs to reach the final goal of an SH [3]. Owners of houses with micro-generation can be considered producers and consumers.

This paper investigates HEMS and DR capabilities as well as the integration of RES, ESS, and EVs in SHs, to minimize clients' electricity costs in an energy community equipped with a local energy controller.

On account of an increase in home appliances' power consumption and the different power variations during the day, new control strategies and HEMSs were intensively developed and optimized in the last few years.

For instance, in [5] a HEMS is suggested to minimize the electricity costs of a home using DR programs as well as a MILP model. The cost decreased when employing these methods while ensuring battery and domestic appliances constraints. Authors in [6] utilize DR programs and a MILP framework-based modelling of HEMS. EVs were considered as a storage unit opportunity via Vehicle-to-Home (V2H) and Vehicle-to-Grid (V2G) options. A small-scale RES, an ESS, and a two-way energy exchange permitted by net metering were combined to reduce electricity costs and assure consumer comfort.

In [7], a smart thermostat is combined with a MILP-based HEMS that executes day-ahead load scheduling, aiming to minimize costs. The results shown were promising, achieving a daily cost reduction under some DR programs. A MILP multi-objective problem can be seen in [8], where the goal is to minimize electricity costs. The proposed model was tested with various price-based DR programs. Simulation results show reductions in electricity costs. In reference [9], a pool trading model in a local energy community is considered. A price-based DR program was incorporated to augment consumers' will to alter consumption habits. The results have shown that electricity cost reduction was higher in an integrated operation mode.

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TABLE I. SUMMARY TABLE OF RELATED WORKS.

Reference	Focus	Objective function	Optimization tool	Devices studied	Energy trading	DR	Type of load
[5]	One home	Min. electr. costs	Mixed-Integer Linear	ESS	No	Yes	Fixed
[6]	One home	Min. electr. costs Min. user discomfort	Mixed-Integer Linear	ESS, RES, EV	Yes	Yes	Fixed
[7]	One home	Min. costs	Mixed-Integer Linear	ESS, EV	No	Yes	Shiftable
[8]	One home	Min. electr. costs Min. user discomfort	Mixed-Integer Linear	ESS	No	Yes	Shiftable
[9]	Energy community	Min. operation costs	Mixed-Integer Linear	ESS, PV, EV	Yes	Yes	Fixed
[10]	One home	Min. electr. costs	Mixed-Integer Linear, Metaheuristic	ESS, RES	No	Yes	Shiftable
[11]	One home	Min. electr. costs Min. user discomfort	Stochastic	ESS, RES, EV	No	Yes	Shiftable
[12]	One home	Min. electr. costs Min. user discomfort	Stochastic	ESS, RES, EV	No	Yes	Shiftable
[13]	One home	Energy selling	PSO BPSO	ESS, RES	Yes	No	-
[14]	One home	Min. electr. costs Min. monthly peak	Mixed-Integer Non Linear	RES	No	Yes	Fixed
This work	**Energy community**	**Min. electr. costs Min. user discomfort**	**MILP**	**ESS, RES, EV**	**Yes**	**Yes**	**Shiftable**

A MILP HEMS is often implemented due to its efficiency in terms of the objective function. On the other hand, this technique may require higher computational time.

According to [10], two different methodological approaches have been studied: MILP and metaheuristic; the latter obtained results farther from the optimal but with a shorter computation time.

Authors in [11] considered EV availability and small-scale RES. A decrease in the electric bill was achieved by using a stochastic model.

In [12], the HEMS considers SH parameters together with customer comfort and cost minimization. The model managed the load system within the constraints of the SH while maintaining comfort levels.

According to [13], a HEMS architecture is proposed with RES and ESS. The results showed that this model was capable to decrease home energy costs. In [14], both HEMS and DR programs are considered to minimize energy costs.

Table I illustrated the summary of related works. In this paper, as a new contribution to earlier studies, an energy community is targeted to minimize both electricity costs and user discomfort. A MILP approach is considered to obtain the global optimal solution, featuring ESS, RES, EV, and DR comprehensively. Load shifting capabilities and energy transactions between the grid and the houses are enabled by the local energy controller, aiming to reduce the final energy bill of the end-users.

Fig. 2 illustrates the local energy community and interconnections between different agents, highlighting the importance of the local energy controller.

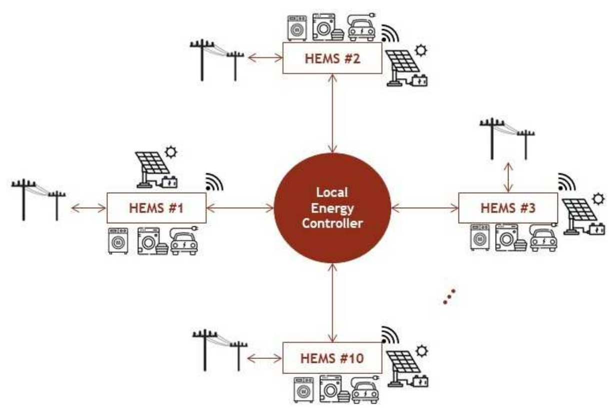

Fig. 2. Energy community and interconnections among different agents enabled by a local energy controller (adapted from [9]).

II. MATHEMATICAL FORMULATION

The objective function (1) of the model developed is to minimize the prosumers daily electricity bills while considering a discomfort penalty in case the prosumer's load is transferred to unwanted time slots. The objective function presents 4 different terms as a single objective optimization problem and it includes: a) first, expected cost of power transactions amid the distribution grid and the HEMS while considering a Time-Of-Use (TOU) pricing mechanism; b) second, start-up and shut-down costs of every appliance; c) third, the discomfort costs of load shifting, which is taken into account when a load is shifted to unwanted periods; d) Fourth and last, the cost of applying an Incentive-Based Regulation (IBR) tariff to the load demand over.

$$
\begin{aligned}
&Minimize\ Z \\
&= \sum_{\omega\in\Omega} \rho_\omega \left(\sum_{t=1}^{NT} \left[\pi_t^{G2H} P_{\omega,t}^{G2H} \Delta t - \pi_t^{H2G} P_{\omega,t}^{H2G} \Delta t\right]\right) \\
&+ \sum_{\omega\in\Omega} \rho_\omega \left(\sum_{i=1}^{NA} \sum_{t=1}^{NT} \left[STUP_{\omega,i,t} C_i^{ST}\right.\right. \\
&\left.\left.+ SHDN_{\omega,i,t} C_i^{SD}\right]\right) - \sum_{i=1}^{NA} \left[C_i^{ST} + C_i^{SD}\right] \\
&+ \sum_{\omega\in\Omega} \rho_\omega \left(\sum_{i=1}^{NA} \sigma\left[DI_{\omega,i}^{+} + DI_{\omega,i}^{-}\right]\right) \\
&+ \sum_{\omega\in\Omega} \rho_\omega \left(\sum_{k=1}^{NK} IBR_k^{Tariff} Energy_{\omega,k}^{Tier}\right)
\end{aligned} \tag{1}
$$

In (1), i is the home appliances index, k is the energy consumption in the IBR mechanism index, t is the time interval of the scheduling index, ω is the scenario index, *NT* is the scheduling period, *NA* is the set of home appliances, Ω is the set of scenarios, ρ_ω is the probability of each scenario, π_t^{G2H} is the hourly electricity price sold to the house, $P_{\omega,t}^{G2H}$ is the power delivered from grid to home, π_t^{H2G} is the hourly electricity price sold to the grid, $P_{\omega,t}^{H2G}$ is the power delivered from home to grid, $STUP_{\omega,i,t}$ is the start-up action binary variable, C_i^{ST} is the start-up cost of shiftable loads, $SHDN_{\omega,i,t}$ is the shut-down action binary variable, C_i^{SD} is the shut-down cost of shiftable loads, σ is the penalty factor for the discomfort index, $DI_{\omega,i}^{+}$ and $DI_{\omega,i}^{-}$ are the discomfort indexes regarding the use of the appliance i after the scheduled time or before the scheduled time, respectively, IBR_k^{tariff} is the stepwise tariff for the IBR mechanism, and the $Energy_{\omega,k}^{Tier}$ is the quantity of energy for each tier in the IBR mechanism.

A. HEMS Scheduling Constraints

The HEMS scheduling constraints are related to the technical and economic restrictions imposed by the algorithm. In (2) it is shown that the total shiftable load at every time slot, $D_{\omega,t}^{Shift}$, is related to the nominal power of the asset, P_i, and its operation is defined by a binary variable $S_{\omega,i,t}$.

$$D_{\omega,t}^{Shift} = \sum_{i=1}^{NA} S_{\omega,i,t} P_i \tag{2}$$

The time authorized to utilize devices is larger than the time required to use them. This is useful when operating with load-shifting capabilities. Hence, the operation standing of shiftable appliances ($S_{\omega,i,t}$) is equal to "0" before and after the time intervals where the use of the assets is authorised by the prosumer and is equal to "1" within these time slots. The binary variable limitations are given by (3) and (4).

$$S_{\omega,i,t} \le \begin{cases} 0 & t < LB_{i,s} \\ 1 & LB_{i,s} \le t \le UB_{i,s} \\ 0 & t > UB_{i,s} \end{cases} \quad S_{\omega,i,t} \in \{0,1\} \tag{3}$$

$$\sum_{t=1}^{NT} S_{\omega,i,t} = T_i \quad \forall i = 1,2,\ldots,NA \tag{4}$$

where $LB_{i,s}$ and $UB_{i,s}$ are the lower and upper bands, respectively, of allowable operation time slots, and T_i represents the total time intervals.

On the right side of (5) is represented the period in which the service of the device is authorized by the owner. Similar constraints can be used to calculate the costs of the base case, as shown in (6).

$$B_{\omega,i,t} = \begin{cases} 0 & t < LB_{i,b} \\ 1 & LB_{i,b} \le t \le UB_{i,b} \\ 0 & t > UB_{i,b} \end{cases} \quad B_{\omega,i,t} \in \{0,1\} \tag{5}$$

$$\sum_{t=1}^{NT} B_{\omega,i,t} = T_i \forall i = 1,2,\ldots,NA \tag{6}$$

where $B_{\omega,i,t}$ is the end-users desired handling status of the appliance, $LB_{i,b}$ and $UB_{i,b}$ are the lower and upper bands, respectively, of the baseline operation time slot.

The main difference between the two constraints is the fact that the binary variable is not used in the authorized time, instead, it is equal to "1" over the operating time of the appliance and "0" during the rest of the time.

A penalty is imposed to avoid superfluous start-up and shut-down of the assets. This is, only one start-up and one shut-down are allowed and any other beyond this will be penalized. It is important to mention that this schedule is not for appliances such as washing machines and spin dryers. Start-up and shut-down variables are defined as shown in (7).

$$STUP_{\omega,i,t} - SHDN_{\omega,i,t} = S_{\omega,i,t} - S_{\omega,i,t-1} \forall t > 1 \tag{7}$$

In (8), for a certain controllable asset, the discomfort index deals with the time intervals for shifted operations.

It is important to note that DI_i^- and DI_i^+ are positive variables; this way, there are no conflicts when the right-hand side of the equation is less than zero.

$$DI_{\omega,i}^{-} \ge \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times B_{\omega,i,t} - \sum_{t=1}^{NT} t \times S_{\omega,i,t}\right] \tag{8}$$

$$DI_{\omega,i}^{+} \ge \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times S_{\omega,i,t} - \sum_{t=1}^{NT} t \times B_{\omega,i,t}\right] \tag{9}$$

To summarize, the optimal scheduling of home appliances requires to be controlled by the HEMS operator following the TOU tariff and the prosumer needs.

The operator is capable of modifying the way controllable loads are managed and costs are minimized accordingly to consumer preferences.

B. Energy Storage System Constraints

The following sub-section aims to explain energy transition limitations between the prosumer and the grid and ESS constraints.

First, in (10), the role of ESS and in-house micro-generation is reflected. The model shown balances the power for each time interval.

$$
\begin{aligned}
&P_{\omega,t}^{G2H} + P_{\omega,t}^{PV} - P_{\omega,t}^{H2G} \\
&= D_{\omega,t}^{Fix} + D_{\omega,t}^{Shift} + \left[\sum_{j=1}^{NS} P_{\omega,j,t}^{Ch.} - \sum_{j=1}^{NS} P_{\omega,j,t}^{Disch.}\right]
\end{aligned} \tag{10}
$$

where $P_{\omega,t}^{PV}$ is the power generated by the photovoltaic system, $D_{\omega,t}^{Fix}$ is the hourly fixed demand, $D_{\omega,t}^{Shift}$ is the demand for the shiftable load by the hour, $P_{\omega,j,t}^{Ch.}$ is the charging power of ESS, and $P_{\omega,j,t}^{Disch.}$ is the discharging power of ESS. It should be noted that $P_{\omega,t}^{PV}$, $D_{\omega,t}^{Fix}$ and $D_{\omega,t}^{Shift}$ are predetermined values, while the rest are variables of the stochastic self-scheduling problem.

In (11)-(12), binary variables are used as a representation of the charging and discharging status of the ESS, $I_{\omega,j,t}^{Ch.}$ and $I_{\omega,j,t}^{Disch.}$, respectively. Thus, to restrict the ESS to be either in charging or discharging mode at one specific time is mathematically formulated in (11), while (12)-(16) are associated with the limitations of the ESS daily operations.

$$0 \leq I_{\omega,j,t}^{Ch.} + I_{\omega,j,t}^{Disch.} \leq 1 \tag{11}$$

Equation (12) restricts the power of charging in the ESS. Hence, when the ESS is in charging mode, $I_{\omega,j,t}^{Ch.}$ value is "1" and the power of charging has to be less or equal to the maximum charging power of ESS $P_j^{Ch.,max}$. Also, (13) assures that when the ESS is in discharging mode, $I_{\omega,j,t}^{Disch.}$ value is "1" and the power of discharging is less or equal to the maximum discharging power of ESS, $P_j^{Disch.,max}$.

$$P_{\omega,j,t}^{Ch.} \leq I_{\omega,j,t}^{Ch.} P_j^{Ch.,max} \tag{12}$$

$$P_{\omega,j,t}^{Disch.} \leq I_{\omega,j,t}^{Disch.} P_j^{Disch.,max} \tag{13}$$

According to a normalized operation of an ESS, the energy stored in it at a certain time is a function of the energy stored in the previous period, plus the results of all of the charging and discharging that happened. This constraint is shown in (14), as well as the efficiency factor of charging and discharging the ESS.

$$E_{\omega,j,t} = E_{\omega,j,t-1} + \eta_j^{Ch.} P_{\omega,j,t}^{Ch.} \Delta t - \frac{1}{\eta_j^{Disch.}} P_{\omega,j,t}^{Disch.} \Delta t \tag{14}$$

where $E_{\omega,j,t}$ is the energy stored in the ESS, $\eta_j^{Ch.}$ is the charging efficiency of the ESS, and $\eta_j^{Disch.}$ is the discharging efficiency of the ESS.

The model presented considers that the initial value of energy stored in the ESS ($E_{\omega,j,1}$) should be secured and equal to the final energy stored in the ESS ($E_{\omega,j,T}$), as shown in (15).

$$E_{\omega,j,1} = E_{\omega,j,T} \tag{15}$$

Equation (16) limits the quantity of energy stored in the ESS, which implies that the system is constrained by a minimum and a maximum limit of energy stored at the ESS denoted as E_j^{min} and E_j^{max}, respectively.

$$E_j^{min} \leq E_{\omega,j,t} \leq E_j^{max} \tag{16}$$

The ESS main role is to make use of the micro-generation system and the electricity of the grid in the most efficient way. Accordingly, it is possible to reduce electricity costs due to the capability of storing energy from the grid or RES when the prices are low, providing it to the home load at peak hours.

Next, (17) and (18) refer to the energy acquired from the grid in each scenario. To calculate the cost of the energy purchased, a stepwise approach is considered according to an IBR tariff. Normally the electricity bill is computed for one month, but it is possible to estimate a value for a day by adapting the tariff in proportion to the quantity of energy during the day. Equation (17) represents the total energy over the scheduled time. Each energy tier is equivalent to $Energy_{\omega,k}^{Tier}$ and the sum of each of them is equal to the total energy in the total time scheduled. The number of energy tiers acquired from the grid is mathematically formulated in (18), it should be taken into account that these tiers do not need to be identical. Bear in mind also that the energy price is exponentially given while the energy tiers are chosen from the cheapest to the most expensive one. $Energy_{\omega,k}^{Tier}$ should always be less than the maximum energy consumption of each tier, $E_k^{Tier,max}$, which is modelled by the binary variable $I_{\omega,k}^{Tier}$, relating to the status of the activated tier in the IBR mechanism.

$$\sum_{t=1}^{NT} P_{\omega,t}^{G2H} \Delta t = \sum_{k=1}^{NK} Energy_{\omega,k}^{Tier} \; \forall \omega \in \Omega \tag{17}$$

$$Energy_{\omega,k}^{Tier} \leq E_k^{Tier,max} I_{\omega,k}^{Tier} \quad I_{\omega,k}^{Tier} \in \{0,1\} \tag{18}$$

To summarize, within the constraints mentioned it is possible to reduce the energy bill of the prosumer by reducing the HEMS reliance on the grid, shifting the load to off-peak hours, and the adaptation of consumption patterns. Moreover, the capability to sell the extra energy produced by RES to the community grid creates some profit for the house owner, reducing, even more, the electricity bill.

III. Numerical Studies and Results

In this section, the use case is presented, which describes all the system data considered to test the mathematical formulation demonstrated in the previous section. Also, a discussion regarding the numerical results of the operational model is presented.

A. Use Case

The proposed model is assessed in this section to exhibit the effective behaviour of a HEMS in ten different scenarios, exhibiting that load-shifting capabilities and energy transactions between the grid and the houses can reduce the final energy bill of the end-users. This use case includes ten houses with different consumption patterns integrated into a local energy community where it is possible to inject power into the grid when there is a surplus of energy.

This model considers that the installed capacity of PV technology on the rooftop of each house is 3 kW. Fig. 3 reveals the PV power generation for ten different scenarios over the day. This model studies forty-eight different time slots given that the data is evaluated daily in thirty-minute periods. The ten different scenarios are generated using historical data and day-ahead meteorological forecasts [15]. It was also considered in this model that every house was equipped with an ESS with a maximum capacity of 4 kW and minimum energy of 200 Wh, as shown in Table II.

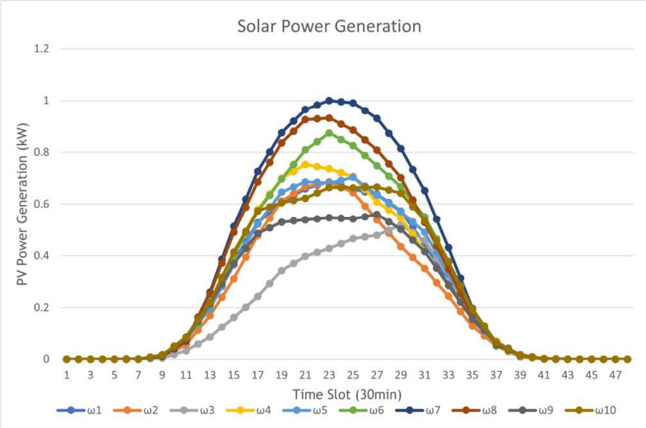

Fig. 3. Solar power generation scenarios considering a 30 min time slot.

TABLE II. ESS TECHNICAL PARAMETERS.

E^{max} (kWh)	E^{min} (kWh)	$P^{Ch.,max}$ (kW)	$P^{Disch.,max}$ (kW)	$\eta^{Ch.}$ %	$\eta^{Disch.}$ %	$E_1 = E_T$ (kWh)
4.00	0.20	0.50	0.50	0.90	0.85	0.20

The ESS has a charging efficiency of 90% and a discharging efficiency of 85%. The maximum charging and discharging power limits are both equal to 500 W.

Fig. 4 shows the IBR tariff used to the different energy consumption tiers. This mechanism is used to restrict the quantity of high energy usage during off-peak periods, to assist in maintaining the grid stable. The tariff is applied to the daily energy injected from the grid to the house.

The DR programs considered in this model are TOU and real-time pricing. Both of them are categorized as price-based voluntary DR programs, meaning that the end-user has the choice of participating in these programs or not. It is important to notice that both programs impact the electricity bill by captivating the consumer to change his normal energy consumption habits.

In this study, it is considered that each prosumer has a predefined load pattern that follows the consumer's preferences. Each house has a different load pattern and an average shiftable load power demand of 30.70 kW.

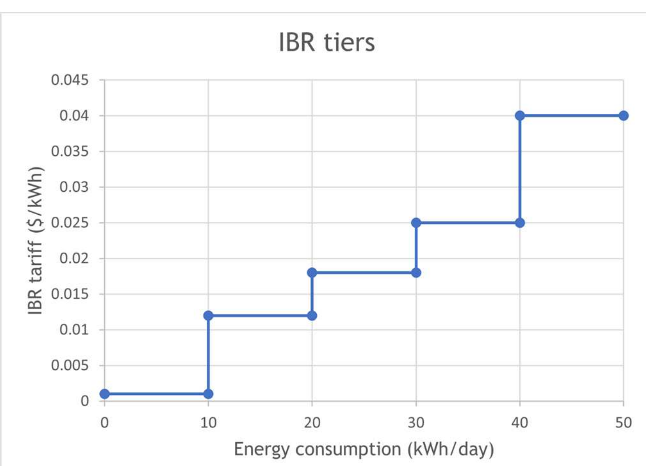

Fig. 4. IBR tariff proportionate to energy consumption.

In the houses considered in this model, the non-shiftable load demand (e.g. lights and refrigerator) must be supplied exactly at a specified time. This means that certain appliances cannot be shiftable and have to work exactly at the time that the end-user wants. The average non-shiftable power demand of the ten different houses is 14.371 kW. Fig. 5 shows the non-shiftable loads of "House A", as an example. As can be seen, the refrigerator works the whole day due to the need to maintain a constant low temperature inside this appliance.

B. *Discussion and Results*

The HEMS studied is a MILP model and the simulation results were achieved by a CPLEX solver through General Algebraic Modelling System (GAMS).

Fig. 6. represents the energy stored in the ESS installed on each house. It is easily noted that this figure has two different constraints, one being the maximum value of energy stored (4 kWh) and the minimum value (0.2 kWh), which can be seen at the beginning and the end of the day. For most of the ten houses, the ESS starts charging in the first hours of the day and reaches its highest value when the PV generation is at its maximum performance.

Fig. 7 shows loads shifted for "House A", as an example, as well as the load power of each appliance. In this house, the EV was charged between times 42 and 47. Hence, the EV was not charged at peak demand periods, which normally occur around time slots 36 to 38. The results were simulated using a penalty factor for the discomfort index equal to 0.002. If this value was higher, there would be less load-shifting capability and, thus, costs wouldn't be as low; however, in this case, the assets would function in the end-users' preferred time slots.

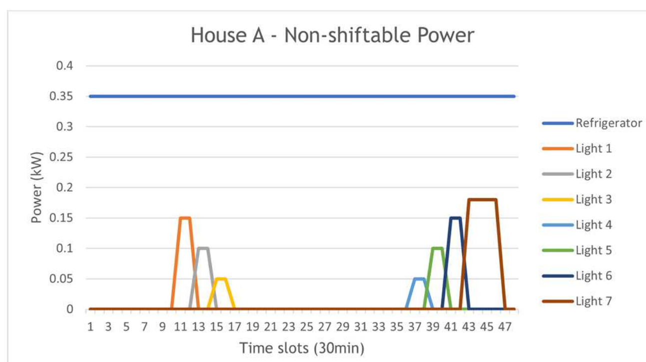

Fig. 5. Non-shiftable loads of house A.

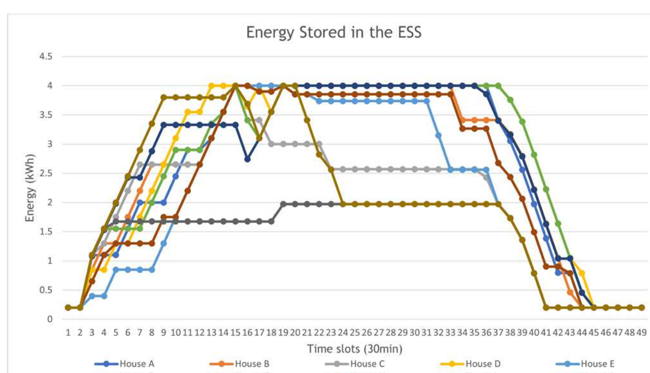

Fig. 6. Energy stored in the ESS.

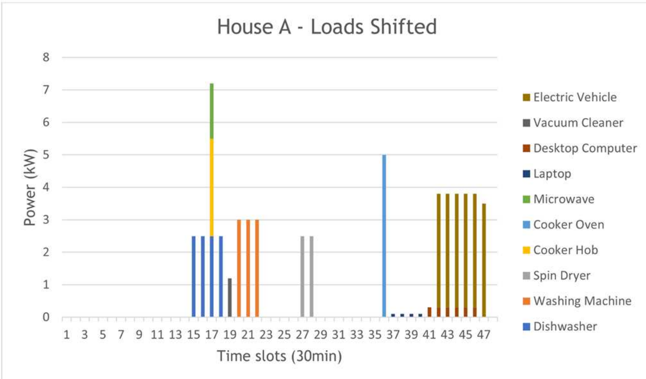

Fig. 7. Loads shifted in House A.

According to the results obtained, it can be confirmed that no assets suffered redundant start-ups and shut-downs while being able to shift loads effectively according to the TOU tariff. This expresses the excellent capability of the model regarding HEMS scheduling constraints and the capability of satisfying end-users' needs.

Next, the energy transactions with the grid of all ten houses are evaluated. Fig. 8 shows the energy injection from the grid to the house in the different time slots. Generally speaking, all ten houses follow a similar behaviour regarding the Grid-to-Home (G2H) injection. The results show that, more often than not, the G2H energy injection is larger at the beginning and at the end of the day. Energy transactions at peak demand time slots like 12 to 19 and 40 to 44 are noticeable, representing 6:00h to 9:30h and 20:00h to 22:00h.

Fig. 9 presents the results of energy transactions from House-to-Grid (H2G). The ten curves show that H2G energy injection occurs on the contrary time slots of the G2H transaction, which respects the fact that the end-user cannot buy and sell energy at the same time. The period of H2G injection is generally from time slot 16 to 37, representing 8:00h to 18:30h, that is, the hours with sunlight. The simulation results confirm that the H2G injection is related to solar power generation.

Keep in mind that the model studies ten different houses integrated into an energy community equipped with a local energy controller. This makes it possible to transact energy between houses to support the different consumption patterns of each end-user. Overall, the model was capable to minimize the daily electricity bill in all cases, proving its proficiency.

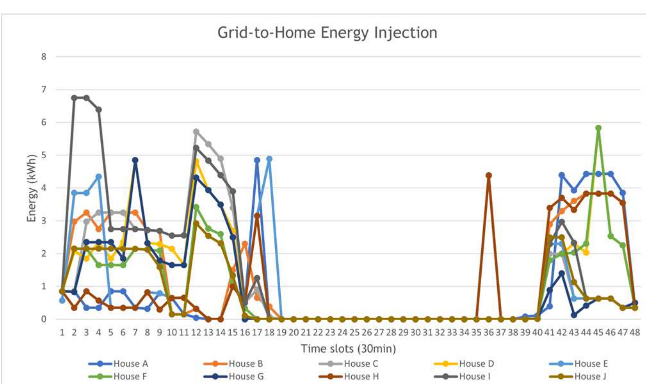

Fig. 8. Grid-to-Home energy transaction.

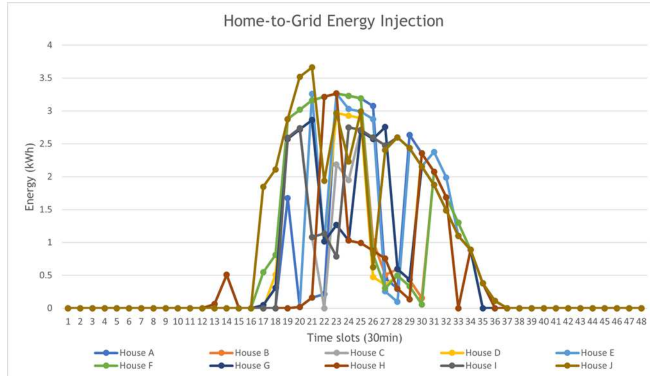

Fig. 9. Home-to-Grid energy transaction.

IV. Conclusions

A HEMS with load-shifting capabilities was modeled in this paper, where the main objective was the daily energy bill minimization while considering end-users' comfort. The case study included a community of ten houses with different load demands integrated with a local energy controller. It was considered that all ten houses were equipped with solar power and ESS, having different shiftable and fixed loads. Load-shifting results with price-based DR programs showed that, with our HEMS model, it was possible to skillfully manage appliance demand to more economically friendly time slots.

V. References

[1] S.S. Gill, *et al.*, “Transformative effects of IoT, blockchain and artificial intelligence on cloud computing: Evolution, vision, trends and open challenges”, *Internet of Things*, vol. 8, 100118, 2019.

[2] Yi Liu, Liye Xiao, Guodong Yao, Siqi Bu, “Pricing-based demand response for a smart home with various types of household appliances considering customer satisfaction”, *IEEE Access*, vol. 7, 2019.

[3] B.N. Silva, M. Khan, K. Han, “Load balancing integrated least slack time-based appliance scheduling for smart home energy management”, *Sensors*, vol. 18, 2018.

[4] H. Shareef, M.S. Ahmed, A. Mohamed, E. Al Hassan, “Review on home energy management system considering demand responses, smart technologies, and intelligent controllers”, *IEEE Access*, vol. 8, 2018.

[5] M. Shafie-khah, *et al*, “Optimal behavior of smart households facing with both price-based and incentive-based demand response programs”, in *Proc. IEEE Manchester PowerTech*, 2017.

[6] O. Erdinc, *et al*, “Smart household operation considering bi-directional EV and ESS utilization by real-time pricing-based DR”, *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1281-1291, 2015.

[7] A.C. Duman, H.S. Erdenc, Ö. Gönül, Ö. Güler, “A home energy management system with an integrated smart thermostat for demand response in smart grids”, *Sustainable Cities and Society*, vol. 65, 102639, 2021.

[8] M.S. Javadi, *et al.*, “Self-scheduling model for home energy management systems considering the end-users discomfort index within price-based demand response programs”, *Sustainable Cities and Society*, vol. 68, 102792, 2021.

[9] M.S. Javadi, *et al.*, “Pool trading model within a local energy community considering flexible loads, photovoltaic generation and energy storage systems”, *Sustainable Cities and Society*, vol. 79, 103747, 2022.

[10] V. Rasouli, I. Gonçalves, C.H. Antunes, Á. Gomes, “A comparison of MILP and metaheuristic approaches for implementation of a home energy management system under dynamic tariffs”, in *Proc. International Conference on Smart Energy Systems and Technologies*, 2019.

[11] M. Shafie-khah, P. Siano, “A stochastic home energy management system considering satisfaction cost and response fatigue”, *IEEE Transactions on Industrial Informatics*, vol. 14, no. 2, pp. 629-638, 2018.

[12] G.J. Osório, *et al.*, “Analysis application of controllable load appliances management in a smart home”, *Energies*, vol. 12, 3710, 2019.

[13] H.T. Dinh, *et al.*, “A home energy management system with renewable energy and energy storage utilizing main grid and electricity selling”, *IEEE Access*, vol. 8, 2020.

[14] F. Luo, W. Kong, G. Ranzi, 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.

[15] M.S. Javadi, *et al.*, “Optimal self-scheduling of home energy management system in the presence of photovoltaic power generation and batteries”, *Energy*, vol. 210, 118568, 2020.