ENERGY MANAGEMENT OF SMART HOMES EQUIPPED WITH ENERGY STORAGE SYSTEMS CONSIDERING THE PAR INDEX BASED ON REAL-TIME PRICING

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ABSTRACT:

The main objective of this paper is to propose the scheduling procedure for the power consumption in smart houses equipped with energy storage devices.The construction of smart houses under the infrastructure of smart grids is one of the most important topics in the field of energy systems. Demand aspect control confers many benefits on both customers and application companies. By the optimal scheduling approach can reduce the electricity bills and enhance the peak to average ratio(PAR).Real-time pricing combined with an inclining block rate (IBR) tariff is used to prevent high power consumption at times of low cost, and to enhance the PAR index. Because the faulty dedication of the nation of the price of garage structures can have deleterious consequences on PAR, a revised method is used to acquire the best solution for the problem. The proposedmulti-objective optimization problem is solved with non-dominated sorting genetic algorithm (NSGA-II) using MATLAB software. Then fuzzy selection is carried out to reap themaximumdesired answer**.**

I. Introduction:

By implementing smart grids and smart home models and facilities, home residents can use this infrastructure to scale back their electricity bills, supported different pricing models. Several models for this process are proposed within the previous couple of year. Local generation and consumption of energy in homes are often organized by building energy management systems (BEMS). These technologies may modify domestic energy use and adjust electricity consumption or production in dwellings. The most important function of smart grids is demand-side management (DSM) system, their main responsibility is to balance of electricity supply and demand in the least times. Demand response schemes like dynamic pricing are meant to shift load consumption from peak periods to off-peak periods. As demand increases, prices are adjusted according to the consumers from consuming at the times of peak consumption, this will minimize costs and ultimately alleviate peak load on power grids. Since the first 2000s, many researchers have focused on demand-side management and control of loads in residential buildings. The most important reason is that energy usage in buildings currently accounts for about 32% of the entire final energy consumption within the world. Smart homes are residential areas equipped with sensors and processors for collecting data, sending control signals in accordance with occupant's activities and expectations.

The total power consumption associated with all appliances was considered, but the separate scheduling for every appliance wasn't addressed. The authors divided appliances based on whether they were interruptible or uninterruptible,so that the results approached more closely to practicaloperation of appliances. However, they didn't consider peak-to- average ratios. The values for electricity cost and peak demandwassimultaneously reduced, but the assumptions of the model were seemed impractical within the case of appliances model and their constraints.

Pricing models are the idea of algorithms in all energy management systems, and every one decisions aboutoperation of appliances are made on the idea of pricing models. Thus, selecting an appropriate pricingmodel is significant. The time-of-use (TOU) model was used because it is the pricingmodel.Inreal-timepricing(RTP) was used together with incliningblockrate(IBR).Though this approach was moreefficient than other models.The energy storage is an important a part of smart home was considered.Demand response (DR) is employed, not only to scale back demand in peak hours,butalso tostop theoccurrenceof latest peaks in off-peak periods. Real-time pricing has problems during this respect, because it leads to the creation of peak hours in low-price hours, which results in increases with in the PAR index. This means that systems may become overloaded during peak hours. Overloadscausesysteminstabilityand outages. To reduce such problems, a mixture of RTP and IBR methods is employedin this paper. In thiscombined model, when power consumption exceeds aintensity, the worth of energy goes up severalsteps within the corresponding hours. Then energy management systems order appliances to scale back theirconsumption during these hours, and daily consumption curves don'tshowanypeakhours.Smoothingload curves are going to be critical in near future under newchallenges like these-calledduckchartissue. Utilization of energy storage devices in new powergrid causes.Thedemandside not onlycan absorb the requested energy but also can save surplus energy in batteries, and sometimes release thatsaved energy to provide the demand side. Storage systems are managed supported energy prices. This means that the state of the charge is said to cost.

During low-price hours, the battery is charged, when the worth of energy is high, the battery is discharge. Thoughthiscausessignificantreductionsinelectricity bills, it's not efficient, even with the implementation of a combined pricing model. That isbecause power consumption in expensive hours is low, and batteries supported the old system shoulddischarge; therefore, home-requested power—from the purpose of view of the grids—becomes lessthanbefore. This strategy can dramatically affect the PAR. So during this paper, a PAR constraint isproposedtosimultaneously improve the PAR index.

This paper proposes a way of scheduling the operating times of home appliances so as to realizeseveral goals:

1) Decrease electricity bills

2) Increase the comfort level of occupants; and

3) Preventviolation of a specified face value.

Thus the most contribution of this paper is to propose a multi-objectivemodel for energy scheduling in smart homes, considering the comfort level of residents and also loadprofile simultaneously and extracting their trade-offs. Please note that the residents have an interest inenergy bills and luxury level while the utilities have an interest in load profile. Also, an innovativecombined pricing model is employed. The tactic also considers batteries as storage devices that help toreduce costs and PAR values.A multi-objective genetic algorithm is employed to unravel the proposedoptimization problem. The results show that the proposed approach is practical and useful for both utilitycompanies and therefore the occupants.Heuristic algorithms are utilized, applied mathematics is employed in optimization problem. The proposed schedulingproblem is nonlinear and multi-objective, so a non-dominated sorting genetic algorithm (NSGA-II) is employed.

1.1. Problem definition:

The aim of the proposed method is to find optimized scheduling for operation times of appliances and state of charge (SOC) of batteries to reach three main goals: minimizing the cost of energy; increasing the satisfaction of occupants; and smoothing the load curve. Under a dynamic pricing model, all of these goals are met.

1.2. Properties and the model of appliances

Occupants prefer that appliances start operating at specific times; additionally, they'll prefer that someappliances finish operating by specific times.For instance, they need to eat breakfast as soon as they getup, therefore the spoon should start operating at that point. As another example, residents may like better tohave dinner as soon as they reach home; hence, they need to make sure that the electrical rice cooker finishes itsjob before they arrive. Each appliance features a different length of operation time (LOT) which will be set by users. P is that the power that appliances consume once they are on. And 'i' is the number of controllablesmart appliances. Thus these parameters are often defined by:

$L = [l_{(1)}, l_{(2)}, l_{(3)} \ldots\ldots\ldots\ldots l_{(i)}] \rightarrow (1)$

$P = [p_{(1)}, p_{(2)}, p_{(3)} \ldots\ldots\ldots p_{(i)}] \rightarrow (2)$

The preferred start time (Alpha) and end time(Beta) are two important parameters that areusefull todeterminethecomfortcriteria.

$Alpha = [\alpha_{(1)}, \alpha_{(2)}, \alpha_{(3)} \ldots\ldots \alpha_{(i)} \ldots\ldots\ldots \alpha_{(l)}] \rightarrow (3)$

$Beta = [\beta_{(1)}, \beta_{(2)}, \beta_{(3)} \ldots\ldots\ldots \beta_{(i)} \ldots\ldots\ldots \beta_{(l)}] \rightarrow (4)$

Minimization of electricity bills may, however, cause dissatisfaction among residents, because someappliances are only allowed to operate at sometimes that are very different from their preferencesinalphaand beta. Due to that, two other parameters are defined that denote minimum start time andmaximum end time; they'recalled eta and gamma. Basically, scheduling is often limited in some desiredtime slots,so as to stop violations of minimum comfort levels. These two parameters preventoperation of appliances before or after specific timesset by users. We denote bounds of operation time (BOTs) as follows:

$Eta = [\eta_{(1)}, \eta_{(2)}, \eta_{(3)} \ldots\ldots \eta_{(i)} \ldots\ldots \eta_{(l)}] \rightarrow (5)$

$Gamma = [\Upsilon_{(1)}, \Upsilon_{(2)}, \Upsilon_{(3)} \ldots\ldots \Upsilon_{(i)} \ldots\ldots \Upsilon_{(l)}] \rightarrow (6)$

These parameters are set as in-home display(IHD) by users and therefore home gatewaysendsthemtoEnergy management controller(EMC) as entrance information, in order to the design and scheduling are oftendepend upon the values. Also, the battery within the charged state acts as an interruptible load. (The modelof the battery is going to be described in next sections). Please note that every home has some manual appliances that can be controlled by using the management system are called controllable appliances. The managing energy is possible for only the controllable appliances but not for the uncontrollable appliances.

1.3. Pricing model:

Real-time pricing may be a special sort of dynamic pricing. It's general enough to be represented as other forms of the dynamic pricing models, like the critical peak pricing (CPP) and time of use pricing (TOU) models. This model can constrain tons of appliances operation at a coffee energy price (EP) time and it's going to cause many problems, like making peak in off-peak time intervals. To stop these, the RTP pricing model combined with IBR is employed to plan a replacement pricing model such it's two different levels for EP within the same time slot, supported the entire power consumption. It is often denoted as follows:

$$\boldsymbol{price(u)} = \begin{cases} \boldsymbol{RTP\ Model\ 0 \leq sigma(u) < \mu} \\ \boldsymbol{penalty\ \mu \leq sigma(u)} \end{cases} \rightarrow \textbf{(7)}$$

Where, sigmarepresents the total power consumption in each and every interval. EP is different from hour tohour, and is said to total power consumption therein hour. If sigma exceeds the boundary of powerconsumption (which is denoted by the pricing model changes the EP to the second pricing level(denoted by penalty); otherwise, the energy price is adequate to the RTP model. it's clear that the secondlevel of pricing is far above the first(RTP). the foremost important positive feature of this combinedmodel is that it can cause balanced power consumption in several time slots. So, it can help control theprofile of power consumption with none peaks in off-peak time intervals.

As mentioned before, the second level of the pricing model is far greater than the standard first level, butit can't be a continuing quantity altogether time units. That's because a while units are in peak intervals, andif power consumption exceeds the limit in these time intervals, the safe and reliable operation of thepower system might be jeopardized [1]. Therefore, it's necessary to line the penalty in these intervals higher than within the others. The model should adjust the penalty value in several time slots. The penaltycan be altered as:

Penalty =λ(RTP)$\rightarrow$(8)

The second level is in direct proportion to the primary level and may be a positive value, meaning that whenever in a day the EP is high, that penalty therein period is bigger than within the others. This model is named combinedRTP&IBR.

1.4. Objective functions and problem formulation:

Consider that 'T_i'is a binary matrix that shows the state of every appliance in several time units. It means that if appliance 'i' in slot u is on, its related member in matrix 'T_i' is 1; otherwise, it is 0. Also, P_i is that the energy matrix of 'i'th household appliance that the dimensions of matrix is adequate to number of your time slots of a day; in other words, it shows the energy consumption by appliances, and s is energy matrix of the battery responsible state.

$$\text{Sigma} = (P_2 + P_2 + \ldots\ldots + P_i) * n \rightarrow (9)$$

It should be noted here that the entire number of in-home appliances is denoted by "i" within the formulations. Each hour is split into n time slots. It's assumed that sigma is that the sum of thePi matrices of all appliances, denoted as equation above. It indicates the whole power consumption in whenever slot. As an example, we will say that if the 55th member of this matrix is adequate to 2.1kW, it means in slot 55, the entire requested power of this house is 2.1kW.Price of energy is characterized by Ca (u) and P (i , u) represents energy consumed by appliance i in time slotu. Thus, the costof electricity for every unit iscalculated by:

$$\text{Cost (P,s)} = \sum_{i=1} \sum_{u=1} P(i,u) * Ca(u) + \sum_{u=1} s(i,u) * Ca(u) \qquad \rightarrow (10)$$

II. SIMULATION RESULTS:

In this study, each hour was divided into number of time slots. As we increases the number of time slots the accuracy of the problem will increases. In this case, the problem has good resolution because the slots are short enough to serve as time units for the operation intervals of all home appliances.Let's consider a smart house consists of six controllable appliances. Among them 1, 2, 3 are uninterruptible, and 4, 5, 6 are interruptible. By using the three dimensional matrix T_i shows the operational situation of each appliance.

The three dimensional are:

The first dimension is related to the solver algorithm.

The second shows time slots during the day; and

The third represents the appliances.

The number between 1 to 6:

$T_i(k, u, i)$

Where k= chromosome number

$1<=u<=120$

$1<=i<=6$

If EMC directs appliance i in slot u to get on, we will denote it by 1. Otherwise, the related member in matrix Ti is adequate to zero. Energy storage systems can participate in scheduling problems, but a minimum level of charge should beretained for technical and reliability purposes. As mentioned in equation (9), Piis called energy matrix that every appliance features a separate one. It's size isequal to the amount of whole time slots during a day. Energy prices—according to the RTP model—areindicated below.

In this section, energy storage and therefore the PAR constraint haven't yet been included within the optimizationproblem. Fig.4 shows the facility consumption of the house with scheduling supported RTP; the opposite profileshows power consumption without BEMS (without optimization). Consistent with this figure, most of the power consumption is shifted to off-peak hours. The reduction within the electricity bill is obvious, but the worth of the PAR during this scenario isn't at an appropriate level.According to Fig. 5, with optimization supported combined RTP & IBR, the height hours from the last profileare distributed in other periods. Therefore, not only the daily cost is reduced compared to the scenario without optimization, but the PARcriterion also improves (based on the RTP model). Although the daily cost increases a touch, the face valueimproves significantly. Therefore, the RTP&IBR pricing model is more efficient than simply RTP. But if residents want to use storage in their homes, this algorithm faces a drag (described within the nextsection).

Note that the ultimate solution from the trade-off region is obtained by applying the fuzzy satisfyingmethod where the reference level for satisfaction of the value and luxury criteria. Scheduling supported RTP.

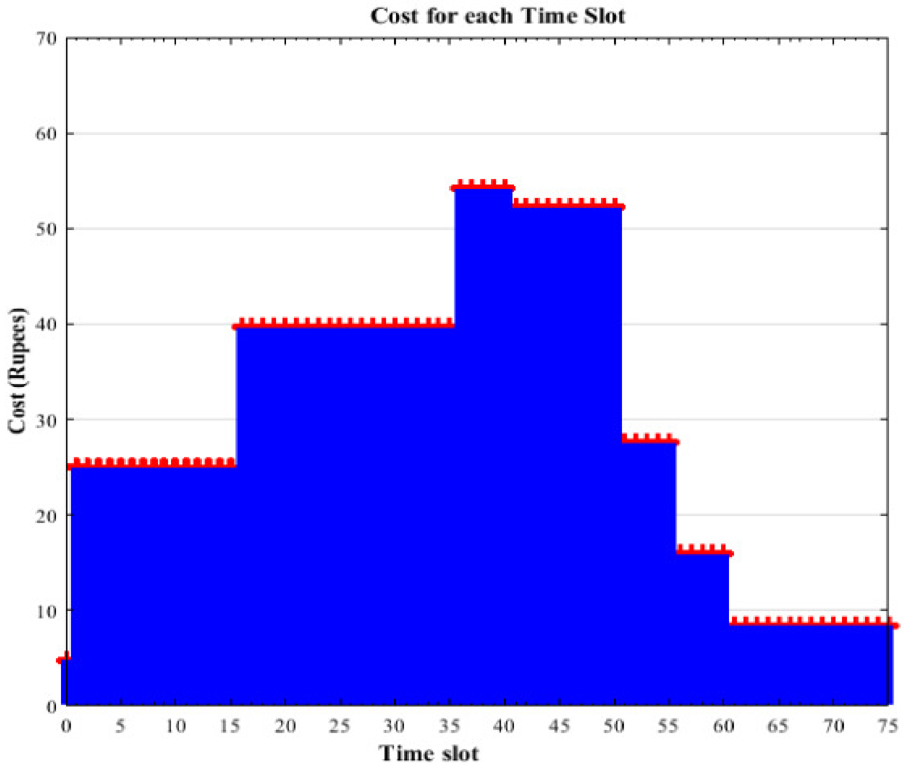


Fig.1. cost of energy supported real time pricing

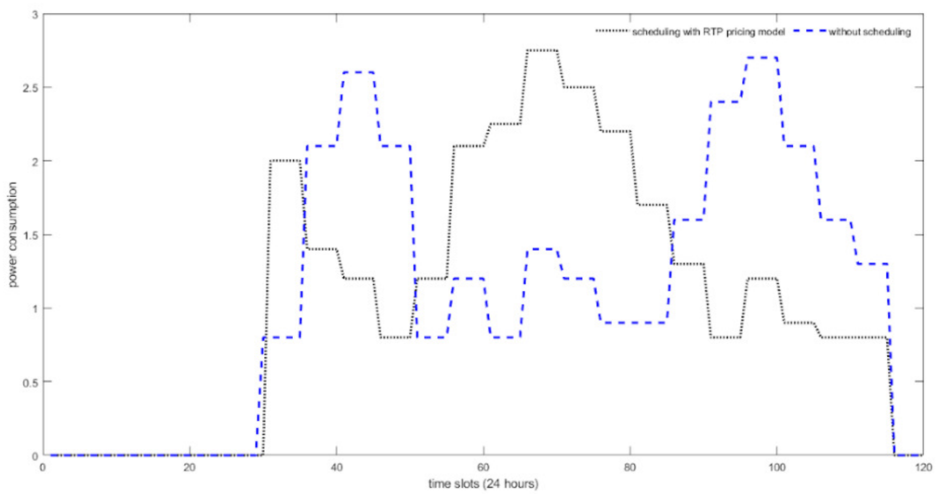


Fig.2. comparison between the facility consumption without optimization and withscheduling based on RTP.

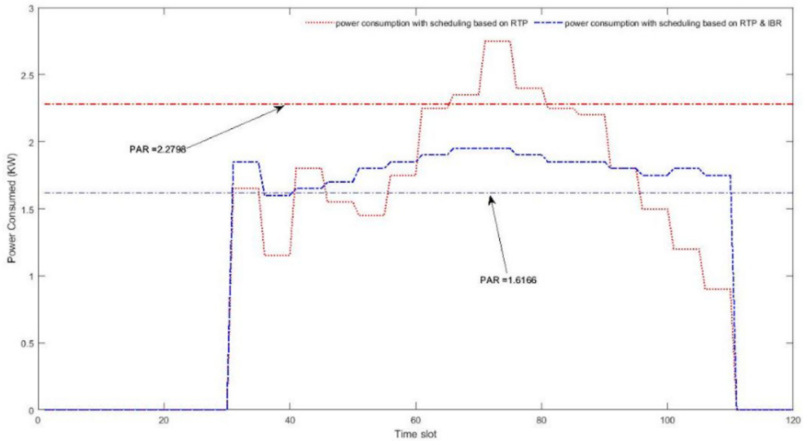


Fig.3. power consumption with scheduling based on RTP&IBR and comparison between the level of PAR with scheduling based on RTP and scheduling based on RTP&IBR.

Effect of Energy Storage Systems

When batteries are utilized in the EMS, there's a discount within the electricity bill, but due to the creation of strong peak hours, this might have deleterious effects on the steadiness of the grid and pose new challengesin system operation. These problems are often solved by balancing home power consumption within thehours of the day. This will be done by setting constraint (22) within the optimization problem.

Fig.6 shows the results of the scheduling problem while considering the batteries with none additional restrictions. The arrows show that peaks and valleys are created by charging and discharging of batteries. Fig. 7 shows the results of adding the PAR constraint (eq.22).Now, with the proposed approach (Fig.7). Although there's a touch increment within the daily cost, the facility consumption profile issignificantly flatter than before.

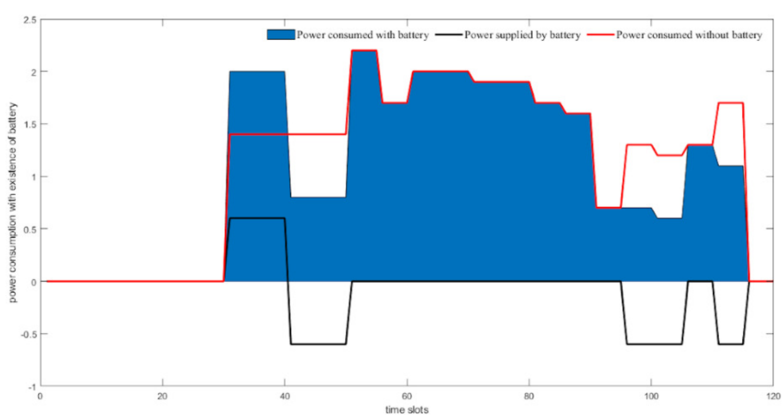


Fig.4. power consumption with existence of battery without applying the PAR constraint and power usage profile

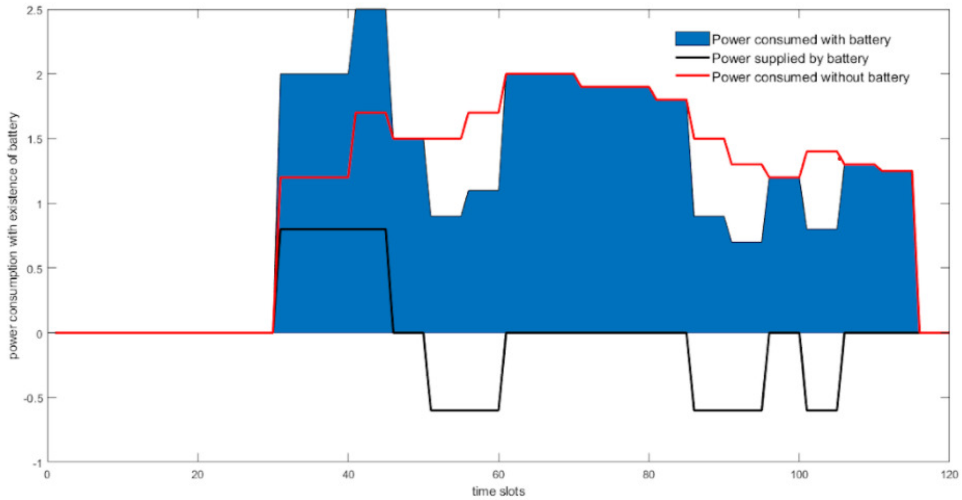


Fig.5. scheduling with existence of battery considering the PAR constraint and power usage profile of the battery (Power supplied with battery).

Power supplied with battery (red dashed line) in fig.7 show the state of battery. When battery is in charge state, it has a positive value; in a discharge state, it has negative value. A scheduling from the knee region of a Pareto set is selected as a final optimal solution by applying the fuzzy satisfying method with values equal to 1 for both reference satisfaction levels [20]. The power consumption profile of this scheduling for appliances and batteries is shown separately in Fig.8.a, and the whole profile is shown in Fig.8. b. This result is related to the knee region; the comfort criterion has higher priority than in the left region results (Fig.7). The values improve when the batteries are considered and the PAR constraint is applied.

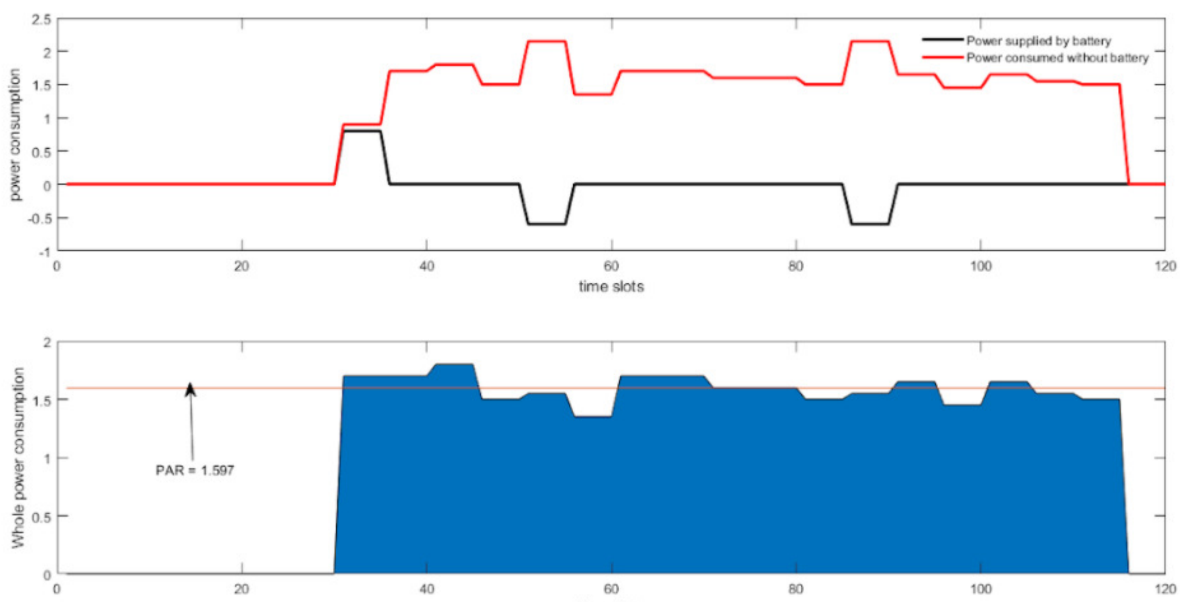
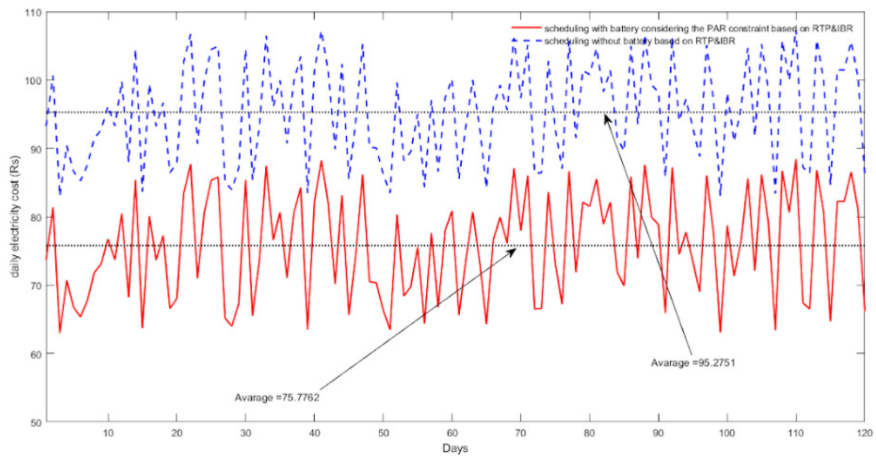
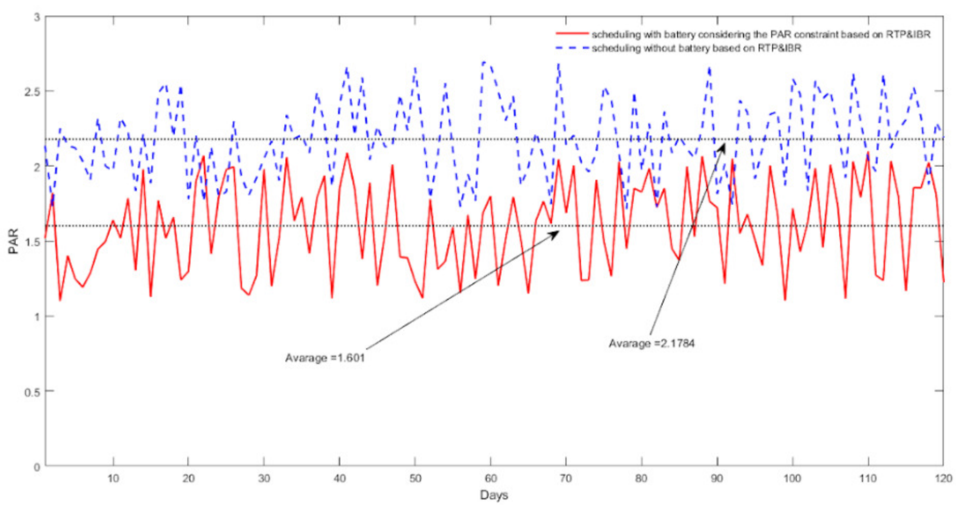


Fig.6. An optimized solution in the knee region. (a): power consumption of appliances (black) and battery (battery usage, red) separately. (b): whole power consumption profile (blue).

A long-term optimization is also conducted for three months under different operating conditions for the appliances the results are shown in Fig.9. These results are obtained with the assumption of equal reference levels of satisfaction for two goals. The first case is optimization without considering batteries scheduling, and the second is optimization considering batteries and with the PAR constraint within four months also both cases are based on the combined RTP&IBR pricing model. The approach proposed in this paper results in significant economic benefits for the EMS and reductions in the PAR value after four months. This means that this algorithm is efficient and practical for implementation in smart homes.



(a)



(b)

Fig.7. Comparison daily electricity cost (a) and PAR (b) between case1: scheduling without battery based on RTP&IBR and case2: scheduling with battery considering the PAR constraint based on RTP&IBR

III. Conclusion:

By this approach we are able to do two goals simultaneously:1) An influence consumption profile that's as flat as possible from the point of view of the most grid; and 2) A discount within the electricity bill. Both these goals are achieved while considering the comfort level of the occupants.

The pricing model, objective functions, and constraints are defined in such how that we will not only achieve a discount within the daily cost and increment of comfort level but also the PAR are often controlled byusing the IBR scheme and therefore the PAR constraint. Also, the ultimate Pareto-optimal set of solutions obtained by the NSGA-II algorithm provides more flexibility for managing the importance of various objectives and resident preferences.

Based on the results of the proposed algorithm, during a smart home with storages the electricity bill and PARvalue are often reduced by considering the satisfaction level of residents by managing storage and energyconsumption. Due to the reduction within the face value, the facility consumption profile on the demand side is balanced at whole-time intervals during the day. The grid then becomes more stable, and theramping costs of upstream grid power plants would be reduced also. Therefore, the implementationof the proposed approach is additionally useful for utility companies. The proposed model might be further developed for a group of smart homes or micro-grids, especially for smoothing the distribution system loadprofile, and consequently reducing ramping constraints and costs within the upstream main grid

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