OPTIMUM POWER SCHEDULING OF A COMMUNITY-BASED HOME ENERGY MANAGEMENT SYSTEM

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ABSTRACT: In a Smart Grid (SG) scenario, domestic consumers can gain cost reduction benefit by scheduling their Appliance Activation Time (AAT) towards the slots of low charge. Minimization in cost is essential in Home Energy Management Systems (HEMS) to induce consumers acceptance for power scheduling to accommodate for a Demand Response (DR) at peak hours. Many proposed algorithms addressed the power scheduling for HEMS but community based optimization has not been the focus. This paper presents Community based HEMS (CHEMS) and targets the minimization of energy costs of the whole community while keeping a low Peak to Average Ratio (PAR) and smooth Power Usage Pattern (PUP). Objective of cost reduction is accomplished by finding most favorable AAT by Particle Swarm Optimization (PSO) in conjunction with Inclined Block Rate (IBR) approach and Circular Price Shift (CPS). Simulated numerical results show that CHEMS can save up to 45.3% electricity cost and achieve 37.98% reduction in PAR for a population size of 750 houses.

ABSTRAK: Dalam senario Smart Grid (SG), pengguna domestik boleh mendapat manfaat pengurangan kos dengan menjadualkan Masa Pengaktifan Perkakasan mereka (AAT) ke arah slot caj rendah. Pengurangan kos adalah penting dalam Sistem Pengurusan Tenaga Rumah (HEMS) untuk mendorong pengguna menerima konsep penjadualan kuasa untuk menampung Sambutan Permintaan (DR) pada waktu puncak. Pelbagai algoritma telah dicadangkan untuk mengatasi isu penjadualan kuasa untuk HEMS tetapi cadangan in tidak menumpukan penyelesaian kepada pengoptimuman melibatkan komuniti. Kertas kerja ini membentangkan HEMS (CHEMS) berasaskan komuniti dan sasarannya adalah pengurangan kos tenaga seluruh komuniti sambil mengekalkan Nisbah Puncak kepada Purata (PAR) yang rendah dan Corak Kegunaan Tenaga (PUP) yang lancar. Objektif pengurangan kos tercapai dengan memperoleh AAT paling baik menggunakan Particle Swarm Optimization (PSO) bersama dengan pendekatan Kadar Inclined Block (IBR) dan Circular Price Shift (CPS). Keputusan numerik simulasi menunjukkan bahawa CHEMS boleh menjimatkan kos elektrik sehingga 45.3% dan mencapai pengurangan PAR sebanyak 37.98 % untuk saiz penduduk sebanyak 750 buah rumah.

KEYWORDS: *smart grid (SG); particle swarm optimization (PSO); community based home energy management (CHEMS); peak to average ratio (PAR); incline block rate (IBR)*

1. INTRODUCTION

Implementation of demand response (DR) has been the prime focus of researchers targeting optimization of smart grids (SG) from the last five years. Surges in power requirements at peak hours are inevitable due to evolution in domestic electrical appliance industry despite advances in renewable energy alternatives. Residential load optimization is a major concern for power utility companies because it constitutes a considerable portion of the total power demand. Domestic users' lack of involvement is one of the hurdles in DR setup for peak load reduction [1]. Additionally, electricity supply companies (ESC) only run their base power production units and secondary units are operated if the power usage pattern (PUP) of the whole grid crosses some threshold. Sharp peaks in PUP lead to higher peak to average ratios (PAR) and result in the need for sub power units to kick in. Operation of sub units for a short span of time caused by frequent peaks in PUP is a technical hassle for ESC, therefore, smooth PUP and reduced PAR is primary goal in demand side management (DSM). Home energy management system (HEMS) is a principal solution for domestic DSM, which involves automated decisions for load optimization [2, 3]. A time-based electricity pricing scheme is an actively used tool for both cost and load curtailment [4, 5]. Numerous strategies have been developed to curtail the power requirement based on DR. Some of them rely on resident habits hence using load prediction models [3, 6, 7] to adjust scheduling, whereas others rely on pricing schemes and penalty terms [8, 9].

In HEMS optimization, the main goal is finding a suitable solution subject to the constraint of electricity PAR reduction. Researchers have formulated a lot of home-based optimum solutions for this problem, some of them are based on game theory [10, 11], mixed integer linear programming [12], genetic algorithm (GA) [8, 13], non-dominated sorting GA [14], particle swarm optimization (PSO) [15], gradient based repair PSO [16], and artificial bee colony optimization [17].

Literature available is based on minimizing the PAR and electricity cost of domestic consumers only based on DR signals. We believe that in a SG paradigm, optimization must be made with regard to small sized communities. A smaller community strengthens the case of SG because it offers relatively shorter paths for renewable energy sharing, which renders low line losses. When a set of houses in a community is subjected to an optimization algorithm, peaks in PUP of whole community are anticipated. Now if some of the houses have renewable energy sources around peaks, they must share their excess energy with houses of the same community due to two reasons: a) it can easily be distributed with less line losses, b) computationally less complicated for optimization algorithm to decide when and with whom to share the excess energy.

In this paper, a community based home energy management system (CHEMS) is proposed, which is better practical for renewable energy sharing between residents of close vicinity. The proposed scheme ensures a reduced PAR and smooth power usage pattern (PUP) for sharp peaked PUPs with reduced electricity cost. CHEMS is based on modification of electricity pricing scheme called Circular Shifted Real Time Price (CSRTP), which scatters consumer device operation slots to achieve reduced PAR.

The remaining paper is structured as follows: Section 2 shows the framework of CHEMS. Section 3 shows the proposed methodology of CHEMS in conjunction with inclined block rate (IBR) and PSO. In Section 4, results are presented. Section 5 is allocated to discussion and analysis, followed by the conclusion in Section 6.

2. FRAMEWORK OF CHEMS

The main aim to develop CHEMS is to lower electricity costs while keeping a reduced PAR. Overall conceptual structure of CHEMS is as shown in Fig. 1. Power is distributed from main grid (MG) to micro grids (MCG) and then each MCG delivers electricity to different communities of equal/variable no. of houses. MCGs can communicate to communities/houses through wired or wireless medium [18] to transmit DR signal. Each house is connected to the MCG via an electricity management controller (EMC) and a smart meter (SM). MCGs have arrangement called as an automatic metering infrastructure (AMI) that can establish two way communications between ESC and consumer. MCGs use AMI to communicate demand response (DR) and other controlling signals to HEMS at peak load time.

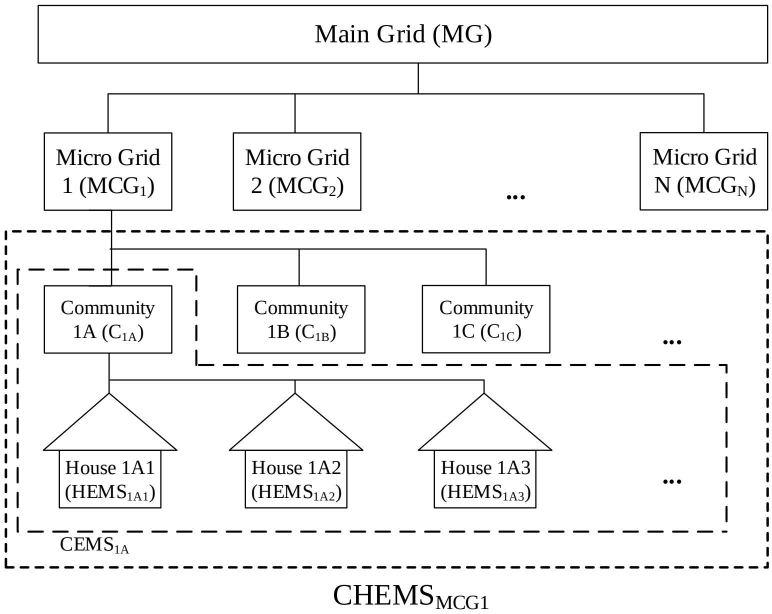

Fig. 1: CHEMS conceptual diagram.

A typical HEMS structure is shown is Fig. 2. In a HEMS setup, there are two types of devices, one regarded as Manually Operated Devices (MODs) and other as Automatically Operated Devices (AODs). In this paper, we consider economizing the operation of AODs only, as the operation timing of MODs cannot be known a day ahead or prior to its operation. Examples of MODs are fluorescent lights, computers, television etc. Such devices are operated manually by the users, hence cannot be used in power scheduling mechanisms. Their power requirements can be used by the SM to be sent to the MCGs for DR computations. AOD comprises the devices that can be activated without supervision, for example air conditioners, rice cookers, water pumps, etc. Electricity Management System (EMS) is fed with the Device Operating Timing (DOT) of each AOD at the start of the day. In this study, it is assumed that the DOT of AODs are previously identified and fed to the HEMS by the residents. Dedicated Interface Devices (DID), computers or smart phones can be used to provide the schedule of AODs to EMS, which can decide the activation of device operation based on the optimization algorithm. Aforementioned knowledge of DOTs is used for scheduling electricity utilization individually at each user EMS. EMS can communicate and control AODs through any currently available solutions such as Zigbee, LonWorks, Z-Wave, X10, INSTEON, KNX or a wired communication link [18].

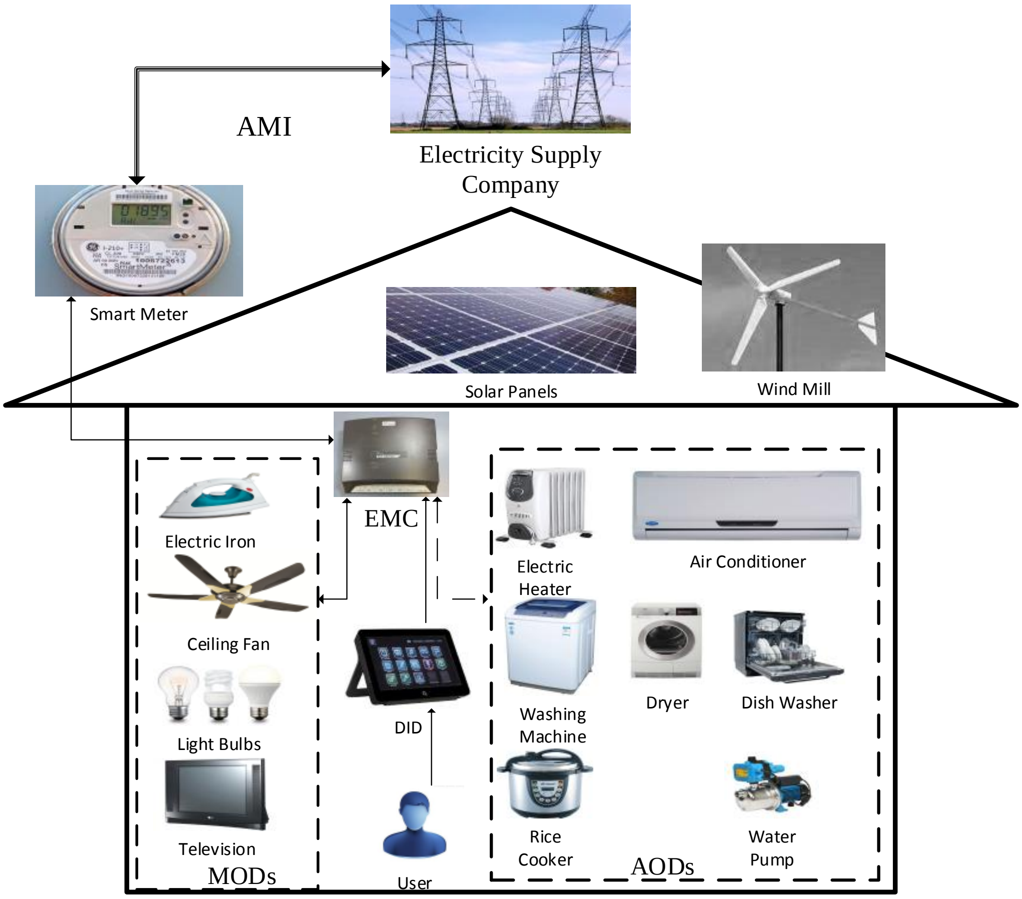

Fig. 2: HEMS structure.

3. PROPOSED METHODOLOGY OF CHEMS USING PSO, IBR AND COMMUNITY BASED PRICING

This section presents the tactic for AODs power scheduling based on PSO combined with IBR and enhanced with CSRTP to accommodate community electricity load curtailments. CSRTP is only used to reduce PAR and make the PUP smooth, unchanged RTP is used for electricity cost evaluation of all communities. An algorithm used for power scheduling AODs is elaborated based on a Real Time Price (RTP) model that charges different rates to each hour of the day. RTP data shown in Fig. 3. is taken from Ameren Illinois Power Company [19].

In an RTP model, the electricity charge to residents is based on one-hour time slots. We have used this data with each hour divided into 6 timeslots of 10 minutes each, such division is made to increase the degree of freedom for power scheduling optimization. Sub divisions of one hour into 6 time slots will result in a 144-slot day. Any AOD can operate for any number of sub divided time slots. For example, if a device has to run for 1.5 hours, it will consume 9 time slots. Each hour can also be subdivided into further smaller time slots, but it is a tradeoff between better optimization results and computational complexity. Smaller size of time slots produces better results as each AOD has more possibilities of being staggered to numerous Activation Time Slots (ATS). A large number of candidate solutions for ATS is a better prospect for cost and PAR reduction but more parameters for optimization consume enormous time for algorithm convergence. On the contrary, if we choose large size of time slots, ATS opportunities are reduced, costs increased, and PAR is inevitable.

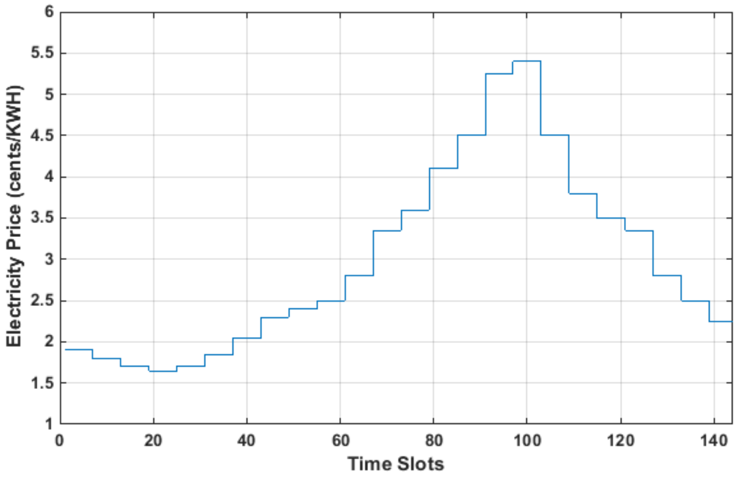

Fig. 3: Real-time electricity prices.

Domestic users are supposed to provide the EMS with the length and possible operating interval of each AOD. Nine devices are considered for a sample house, where some devices may or may not run, and some may run repeatedly on a given day of the month. PUP of all devices will take the form given as a vector:

$$PUP_i = \left[P_i(1) \quad P_i(2) \quad \dots \quad P_i(144) \right] \times P_i \tag{1}$$

Where consumption of power by ith device is given by:

$$P_i = P_i' / 6 \qquad Power / KW \text{ Time Slot} \tag{2}$$

Each device has the power rating in the form of:

$$P_i' = Power / \text{KWH} \tag{3}$$

Once the EMS has received the ATS, Operation Termination Slot (OTS), Operation Time Length (OTL), Device Operation Time Start (DOTS), and Device Operation Time End (DOTE) of every device, it will create a Power Usage Pattern (PUP) of (1) for each AOD using:

$$P_i(j) = \begin{cases} 0 & j < ATS_i, j > OTS_i \\ 1 & ATS_i \leq j \leq OTS_i \end{cases} \tag{4}$$

Where 0 represents the AOD being inactive and 1 represents the AOD being active at corresponding time slot. ATS of each device is constrained by the house resident defined limits as:

$$DOTS_i \leq ATS_i \leq DOTE_i - OTL_i \tag{5}$$

Then the PUP for whole house is calculated as:

$$PUP = \sum_{\forall i} PUP_i \tag{6}$$

Here we have summed up the power consumptions of AODs. Cost of Electricity can be calculated by taking an inner product of (6) and RTP mapped onto 10 minutes time slot. The final objective function of problem at hand is given by:

$$min(PUP.\mathrm{RTP}) \tag{7}$$

We need to minimize (7) subject to (5). When this problem is subjected to any optimization technique, OTL vector of AODs looks for an optimum permissible slot in the day, and it tends to move towards lower rate slots. Likewise all AODs shift towards the time slots with lowest rates, which result in reduced electricity cost but also create higher PAR, which should be avoided. One solution to this problem is a penalty term, which is also used by researchers in the form of IBR [8].

3.1 Particle Swarm Optimization (PSO)

PSO is an iterative process that initiates its optimization by assigning the initial values of particles and their velocities. PSO is applied to this problem for optimization of all ATS for a given house subject to the constraint of "OTL must be covered up with in the range of DOTS and DOTE". Initial values of particles for this optimization are used as the provided DOTS. Cost function is evaluated and the location of the best particle is saved. At the next iteration, new velocities are evaluated, followed by cost function assessment and best particle storage. This process is continued until a termination condition is reached.

3.2 Inclined Block Rate (IBR)

In an IBR approach if a PUP crosses a threshold at any time slot, the rate in RTP is scaled with a factor $\gamma > 1$ for that particular time slot; otherwise if the PUP remains below the predefined threshold, then the rates are unchanged. It works as a controller term to keep optimization parameters from making large PAR. Consider the case represented in Fig. 4.

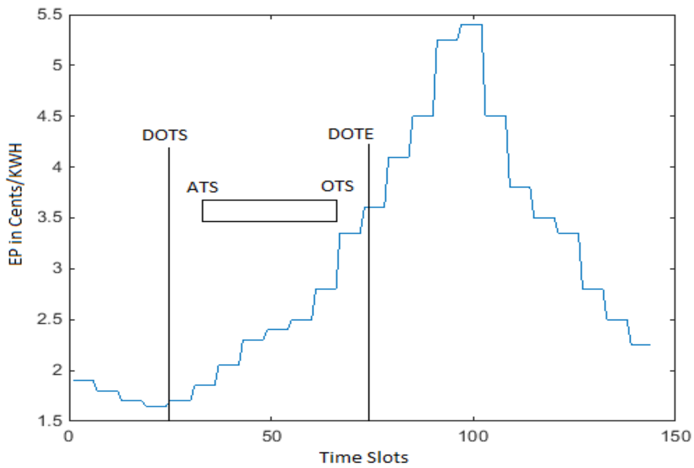

Fig. 4: Device ATS constraints.

The AOD is shown in a rectangular block; its horizontal length shows the OTL of the device, DOTS and DOTE marked as vertical lines. When this device is subjected to an optimization algorithm; its ATS will tend to move towards DOTS as it will cover its DOT over the slots of low Electricity Price (EP). If more than one device for a house operates around that specific slot, they will create a peak PUP by converging towards the vicinity of lowest EP slot. Same peak PUPs can also be created by other residents when they look to run their Floating Operating Time (FOT) based devices to run around the lowest EP slots. FOT refer to those devices which have to run for a specific length of time once a day, e.g. Water Pumps, Washing Machines, and Dryers. Such situations can be controlled by implying IBR.

3.3 Architecture of CHEMS

In a practical scenario of actual population, each added residence is a contributing factor towards a high/peaked PAR in extension to aforementioned aspects of PAR increments. An MCG providing electricity to a large set of consumers can be considered for clarification. The majority of the houses will cluster ATS of their AODs around the time slots of low EP when subjected to optimization through traditional HEMS. This will result in sharp peaks in overall PUP for the corresponding MCG. The core reason for traditional HEMS to cluster AODs is that each house is optimized independently without any information regarding cluster locations of neighboring residents. This phenomenon is not different for any of the available schemes in the literature. Additionally, all of the houses cannot be optimized in one go. This is equivalent to one big house with a very large quantity of devices, which is not practically realizable from two points of views. i) penalty terms for PUP crossing thresholds will not be applicable for separate houses. ii) a large quantity of ATS timings will not allow the optimization algorithm to converge due to time limitations.

CHEMS is the solution for electricity cost and PAR reduction for large populations. Conceptual setup of CHEMS is shown in Fig. 1. The whole set of users under one MCG is divided into several communities. Each community consists of a small number of houses, that can be varied based on the objective. The PUP of every house is optimized separately with application of PSO, IBR, and CSRTP. Every community is offered the same RTP but with a small circular shift, which guides communities to shift their peak loads with small steps. When sharp peaks of individual communities are a small step apart, PAR is automatically reduced. This process ensures reduced PAR and smoothed PUP.

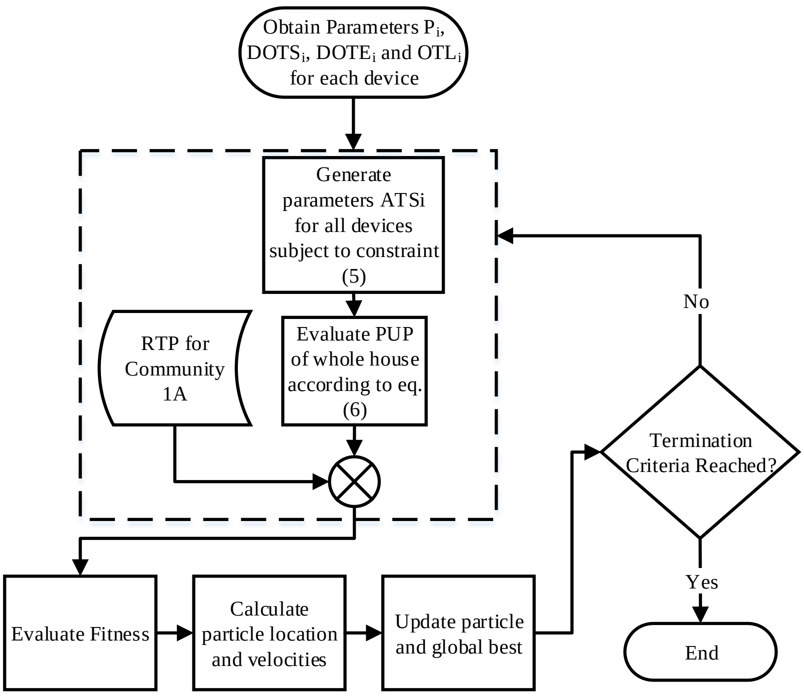

Fig. 5: Flowchart of whole optimization process of one house.

When the PUP of an entire community set is optimized in this fashion, it results in a decreased and smooth curve. Community A is done first and rest of the communities follow thereafter. Let us consider the devices with DOTS and DOTE containing TS_j, being taken as the lowest EP slot in the interval. When the ATS of AODs corresponding to community A are subjected to the optimization algorithm, a peak will be created at TS_j. Then comes the optimization of community B, which being offered a circular shifted RTP will find the lowest EP slot TS_j shifted by k units and positioned at TS_{j+k}. AODs of community B will create a peak at TS_{j+k} by occupying ATS there. This process goes on with rest of the communities and results in a PUP with reduced PAR for the whole MCG. Flowchart for overall optimization process is depicted in Fig. 5.

4. SIMULATION RESULTS

This section is dedicated for simulation results to prove the capability of CHEMS to produce better results for large populations. As MODs are operated at random by the residents, therefore, only AODs are simulated for this demonstration. A maximum of 16 devices can be operated for one residence and a minimum of 8. Some devices like rice cookers may be used more than once a day. A typical residence AOD usage is depicted in Table 1.

Table 1: Typical Residence usage of AODs

AOD	Power (KWH)	OTL (Time Slots)	Operation Slots (Scattered B/w)
Air Conditioner	1.2	4,6,8,…	30 to 144
Electric Heater	1.5	5,10,15,…	100 to 144
Washing Machine	0.5	4,8,10	1 to 70
Clothes Dryer	0.7	4,8,10	71 to 100
Dishwasher	0.5	2,4,6	120 to 144
Water Pump	1	3,6,9	70 to 90
Electric Kettle	1.6	1,2	60 to 70, 90 to 110
Rice Cooker	0.5	2,4	1 to 30, 50 to 70, 95 to 110

For this research, all simulations are performed in MATLAB. PSO optimization parameters are the swarm size of 100, minimum fraction for neighbors 0.25, number of variables equal to number of devices, tolerance value for relative change 10^{-6} and termination after 3200 iterations.

Results are compared with optimization based on a standalone house with traditional RTP, hence it is called traditional HEMS. Traditional HEMS is optimized with PSO & IBR applied to each house, whereas, CHEMS use a modified RTP scheme in addition to PSO and IBR. In this modeling, we took a total of 500 and 200 houses with randomized loads based on Table 1. Altered population sizes were chosen to study the effects of community size on different populations. The community size directly affects the final PUP, so different sizes of communities are considered and the outcomes are shown in Fig. 6 for the population size of 500 houses.

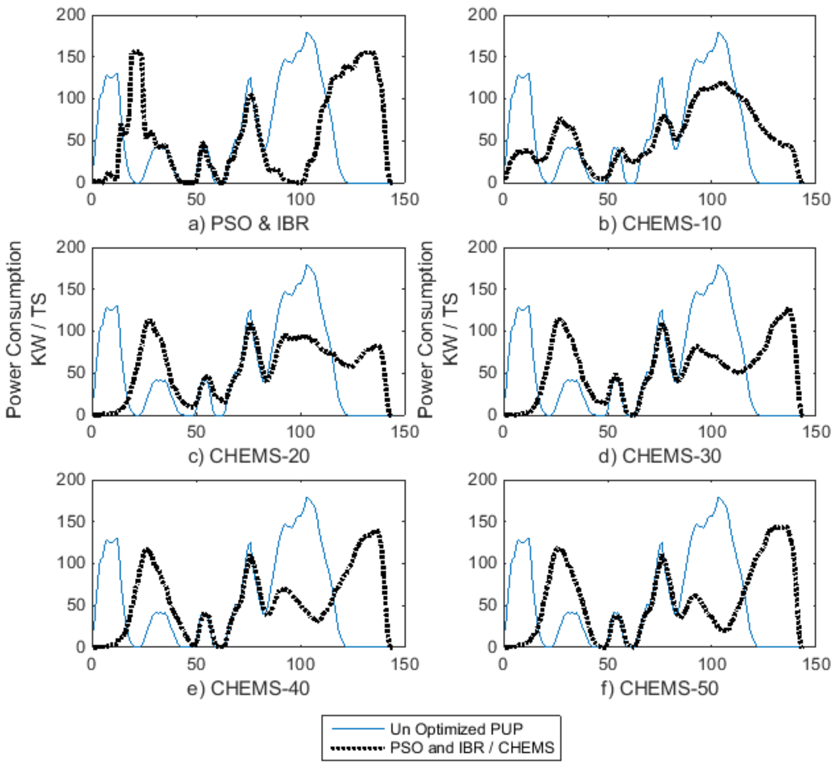

Fig. 6: Simulation with 500 houses a) Traditional HEMS optimization b), c), d), e), and f) CHEMS with 10, 20, 30, 40, and 50 houses/community.

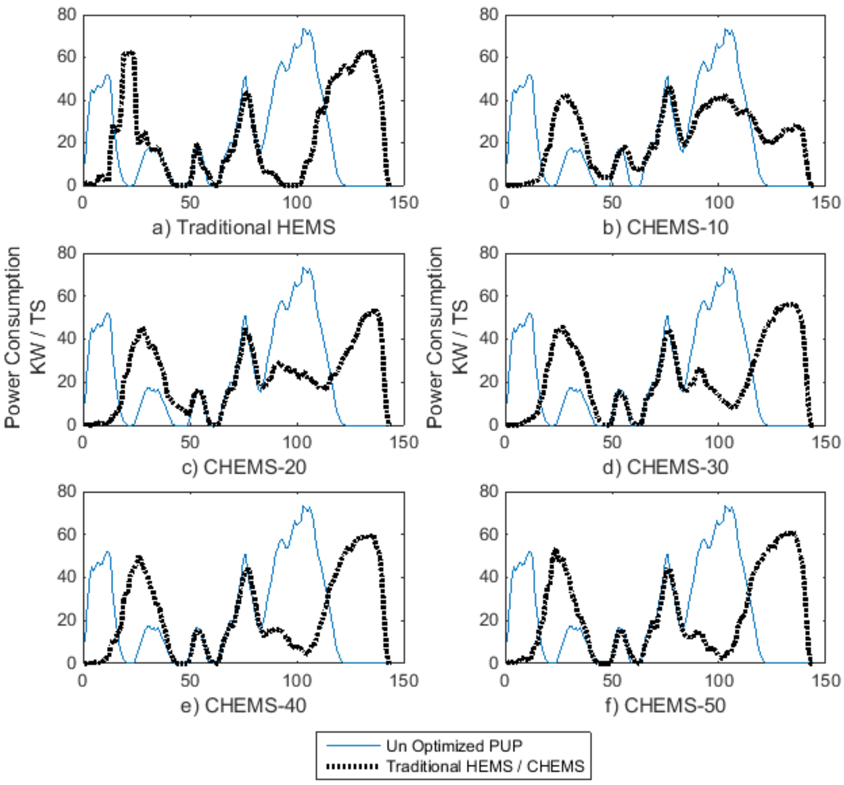

Fig. 7: Simulation with 200 houses a) Traditional HEMS optimization b), c), d), e), and f) CHEMS with 10, 20, 30, 40, and 50 houses/community.

Each sub-figure of Fig. 6 consists of two graphs. One of them is common to all sub-figures showing PUP without any power scheduling. The second graph, in dotted form, is of PSO with IBR only in Fig. 6a. Figure 6b, 6c, 6d, 6e, and 6f represent application of CHEMS with community sizes of 10, 20, 30, 40, and 50 houses per community. The same procedure is repeated for the population size of 200 and shown in Fig. 7. Reduction in PAR is 12.22% and electricity cost is 47.1% for traditional HEMS when a population size of 500 houses is considered. Whereas application of CHEMS with 10% houses per community, PAR is reduced by 25.56% and electricity cost reduced by 45.94%. Figures 6 and 7 show that rapid changes in PUP are eliminated by application of CHEMS for both population sizes.

Smaller community size means larger shifts in RTP and results in increased delay time for consumer device operations. Therefore, small shifts are used in CSRTP. Results are evaluated for different sizes of communities but 10% houses per community is recommended to keep the device operation delay time as low as possible. Complete results for population sizes of 200, 500 and 750 houses are summarized in Table 2. From Table 2 it is clearly evident that CHEMS enhances results of optimization by PSO applied in conjunction with IBR. CHEMS lags by 1.05% form traditional HEMS in electricity cost reduction for population size of 200 houses and it leads traditional HEMS by 2.72% in PAR reduction. For a population size of 500 houses, CHEMS lags by 1.17% from traditional HEMS in electricity cost reduction and leads it by 13.34% in PAR reduction. Finally, for a population size of 750 houses, traditional HEMS is less than 2% better than CHEMS in terms of cost reduction, however, CHEMS outsmarts traditional HEMS based optimization by 25.08% when PAR reduction is considered. This trend shows that results of CHEMS are enhanced with larger populations, which is the case of real world.

CHEMS produces best results in terms of PAR reduction with community sizes of 2% houses/community and optimal results for cost reduction are achieved with a community size of 10% houses/community. The tradeoff between electricity cost and PAR reduction can easily be managed using variable community size at times of peak power demand. PAR reduction takes priority when electricity power demand is higher than a threshold; hence smaller community size may be used by ESC. Large community size can be selected if cost reduction is at ESC precedence.

Table 2: Simulation with 200, 500 and 750 houses

Algorithm	**Community based on number of houses (Percentage)**	**Percentage PAR Reduction**			**Electricity Cost Reduction Percentage**		
		200 Houses	**500 Houses**	**750 Houses**	**200 Houses**	**500 Houses**	**750 Houses**
Traditional HEMS with PSO & IBR	Nil	14.74	12.22	11.93	47.08	47.11	47.26
CHEMS with PSO & IBR	2%	37.19	36.57	38.61	36.71	38.02	39.27
	4%	27.21	37.97	34.15	41.78	41.45	40.76
	6%	23.13	36.94	37.29	44	42.34	41.92
	8%	18.59	37.13	37.23	45.46	44.56	43.97
	10%	**17.46**	**25.56**	**37.01**	**46.03**	**45.94**	**45.3**

The rest of the comparisons of traditional HEMS with CHEMS are based on 10% houses/community. Figure 8 shows the comparison of PAR reduction capabilities against different population sizes. PAR is almost the same for both CHEMS and traditional HEMS up to a population size of 100 houses. When the population size is greater than 100, PAR is almost constant for traditional HEMS. CHEMS reduced PAR with increase in population size after 100 houses and stabilized after 650 houses. PAR is reduced to 2 by CHEMS, whereas traditional HEMS only reduced it to 2.9 from 3.3.

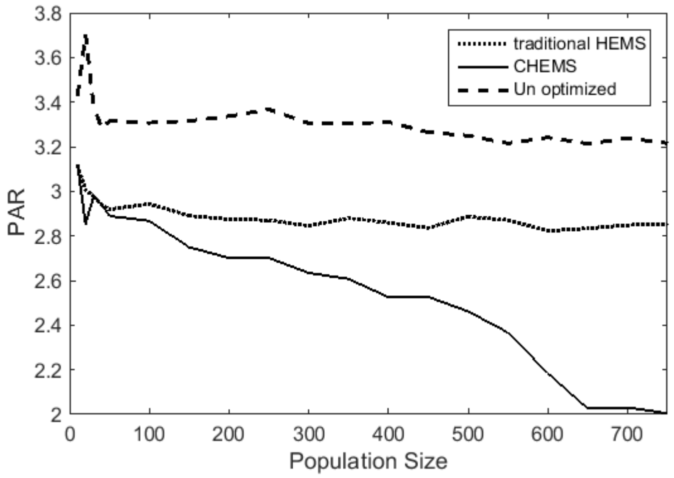

Fig. 8: PAR Comparisons for population of 10 to 750 houses.

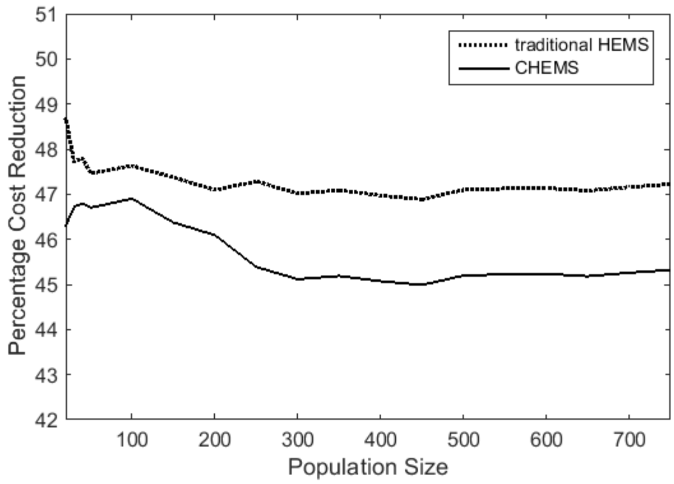

Fig. 9: Percentage cost reduction for population of 10 to 750 houses.

Figure 9 shows the percentage cost reduction for both schemes. Traditional HEMS is slightly better than CHEMS from a percentage electricity price reduction point of view. Some lag in cost reduction for the sake of better PAR is obvious because if all consumers cluster around low EP, then PAR reduction is limited as is the case of traditional HEMS optimization.

5. DISCUSSION AND ANALYSIS

This study has demonstrated a new approach of DSM that is based on division of population into communities. Each community is offered a slightly different CSRTP, which renders PUP peaks to scatter around slots of low EP such that overall sharp peaks are eliminated. The algorithm presented does not require any modification in hardware setups available in literature. It can be implemented in HEMS schemes equipped with

ZigBee and sensor network-based appliance control/communication architecture like [20, 21].

The main goal of PAR reduction is achieved with a supplementary benefit of smooth PUP. PUP is smoother with application of CHEMS than traditional HEMS as shown in Fig. 6 and Fig. 7. CHEMS offers more authority to ESC for electricity load shaping and curtailment. ESC can guide consumer EMS to shift loads in PAR reducing manner seamlessly by CSRTP. Variation in community size allows ESC to prioritize between PAR or cost reduction depending upon power generation constraint.

6. CONCLUSIONS

This paper has presented an arrangement for implementing DR in a manner that can easily incorporate the resource sharing factor of SG. It has demonstrated through simulated results that our proposed technique trims PAR exceptionally well and reduces electricity cost with a supplementary benefit of smooth PUP. It is evident from Fig. 6 and Fig. 7 that the PUP transitions are much smoother after optimization by CHEMS. Results summarized in Table 2 show that the PAR reduction with CHEMS is 24% better than traditional HEMS for a community size of 750 houses. Figure 8 shows that CHEMS can reduce PAR for large populations in contrast to traditional HEMS. Cost reduction is almost equivalent as shown in Fig. 9. Additionally, the community-based setup is very suited to localized sharing of renewable energies within the community.

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NOMENCLATURE

MOD	Manually Operated Devices
AOD	Automatically Operated Devices
DOT	Device Operating Time
ATS	Activation Time Slot
OTS	Operation Termination Slot
OTL	Operation Time Length
DOTS	Device Operation Time Start
DOTE	Device Operation Time End
PUP	Power Usage Pattern