A Generic Demand Side Management Model for Smart Grid

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Abstract—Demand Side Management (DSM) is one of the most important aspects in future smart grids: towards electricity generation cost by minimizing the expensive thermal peak power plants. The DSM greatly affects the individual users’ cost as well as the per unit cost. The main objective of this paper is to develop a Generic Demand Side Management (G-DSM) model for residential users to reduce Peak-to-Average Ratio (PAR), total energy cost and Waiting Time of Appliances (WTA) along with fast execution of the proposed algorithm. We propose a system architecture and mathematical formulation for total energy cost minimization, PAR reduction, and WTA. The G-DSM model is based on Genetic Algorithm (GA) for appliances scheduling and considers 20 users having a combination of appliances with different operational characteristics. Simulation results show the effectiveness of G-DSM model both for single and multiple users scenarios.

Index Terms—Demand side management, genetic algorithm, load shifting, smart grid

I. INTRODUCTION

Energy efficiency in smart grid distribution networks through modern Information and Communication Technologies (ICTs), is one of the important focus area of research community [1]. The main steps towards energy efficiency in development of distribution network are Advanced Metering Infrastructure (AMI) and new demand management policies.

DSM programs are developed for end users to efficiently manage their loads. These programs encourage users to shift their load from peak hours to off-peak hours by providing different economic incentives [2]. Early DSM programs were based on unidirectional communication from the power utility to the end users such as Direct Load Control (DLC) [3]. The DLC is most effective for those users having high power consumption appliances. However, the DLC has little effect on users having many low power consumption appliances. There are two major types of Demand Response (DR) programs: Incentive based (DLC) and dynamic pricing (Real time Pricing (RTP) and Time-Of-Use (TOU) Pricing). In case of these pricing schemes, the users are encouraged to voluntarily manage their loads in order to avoid peak load conditions [8]. Several techniques have been developed to address different aspects of DSM as discussed in [4]-[12]. The main objective of DSM techniques discussed in literature, is the reduction of total electricity cost and PAR.

Various optimization techniques have been used for scheduling based DSM schemes such as mixed-integer linear programming [4], game theory [5], or backtracking algorithm [10]. However, evolutionary algorithms [12] show better results because of its flexible nature, that allows the implementation of individual’s life style based load patterns in order to minimize the inconvenience of the users. In [13], evolutionary algorithm is compared with simulated annealing and greedy search method, which shows better results. The evolutionary algorithm such as GA, finds out an optimal schedule for appliances by applying nature inspired processes like crossover, mutation and survival of the fittest. After applying GA, best schedule is achieved for each time frame while meeting the constraints of the problem. The execution time of GA depends on the number of iterations, therefore we want to terminate further processing when an optimal solution is achieved. In our proposed GA based scheduling, the termination criteria is the maximum number of generations (500) which shows better results.

In this paper, GA based approach is used for appliance scheduling in the smart grid environment. GA schedules appliances according to RTP information received from the power utility. The power consumption in a specific time frame is managed by load shifting based strategy instead of load reduction. Appliances are categorized according to their characteristics and users’ preferences. The Energy Management Controller Unit (EMCU) schedules only those appliances which can be delayed. Both single and multiple users cases are considered for simulation.

The remaining paper is organized as follows. Related work and motivation are presented in Section II. Problem formulation is carried out in Section III, and simulation results along with the discussion are described in Section
IV. Paper is concluded in Section V.

II. RELATED WORK AND MOTIVATION

A three layered autonomous DSM model is presented in [3], and consists of: Admission Controller (AC), Load Balancer (LB), DR manager and Load Forecaster (LF). In this model, appliances are categorized according to the requirements of user. For example, the operation of an appliance may be advanced to avoid peak load periods by utilizing the functionalities of LF. The simulation results show the effectiveness of this model. However, when the number of appliances requests exceed from a certain level, then the proposed three layered model cannot ensure power capacity limit. For residential Energy Consumption Scheduling (ECS), Mohsenian, et al. [4] used the idea of game-theory and a distributed algorithm based optimization is applied on different aspects of ECS. The authors consider a pricing mechanism based on convex and increasing cost function. The objective is to minimize PAR, total cost and individual’s user cost. In [5], a new pricing method known as Vickrey-Clarke-Grove (VCG) mechanism is proposed. The mechanism aims to increase the social welfare (maximizing the cumulative convenience of all the users and minimizing the cost imposed on them), and encourages users to shift their load from peak hours to off-peak hours. The purpose of adopting this method is to achieve efficiency, non-negative transfer (i.e., payment from utility to user) and truthfulness among users. Besides obtaining a social welfare, the utility also gets benefits of obtaining a reduced average load shape curve. Weighted average filter based price prediction functionality is discussed in [6]. In which, price predictor and energy scheduler are considered within a smart meter and Inclining Block Rates (IBR) is combined with RTP for billing mechanism. Different performance parameter are explained and the simulation results show better performance.

All of the previous techniques consider users with a fixed load curve. However, load uncertainty is a big challenge, especially in designing a pricing mechanism. This important issue is considered in [7], which adopts DSM model that forecasts the load curve of the user from previous knowledge of their energy usage. The proposed design is multi-stage, i.e., information related to appliances is revealed over time. Load categorization and problem formulation are explained in detail and load synchronization problem is also avoided. Simulations show improved results due to reduction in PAR and energy cost. Two most effective and related ideas, i.e., fairness and optimality are addressed in [8]. The authors present an alternative pricing scheme by combing RTP with hour by hour billing mechanism. In this scheme, the electricity bill of each user not only depends on his own load profile but also on other users’ profiles because, they all effect the overall cost of the power system. The work is identical to [4], in which the authors developed a game theory based problem formulation to minimize PAR and total energy cost. The proposed work is 73% more efficient in fairness and also shows that fairness is inversely proportional to optimality. However, other well-known issues such as, PAR and energy cost are not explored.

Another ECS for DSM is proposed in [9] which is based on artificial intelligence technique known as backtracking algorithm. Authors have explored PAR reduction and execution time of the algorithm for residential type users. However, other issues regarding fairness, coverage area and WTA are not considered. To achieve effective DSM, pricing scheme also plays an important role. Incentives are provided to users to encourage them to schedule their loads efficiently [10]. This is practically possible if the utility company provides information about electricity price some hours ahead of usage time. ECS unit must also be capable to predict price to control load in real-time electricity pricing environment. Whereas in [11], a heuristic optimization based DSM is adopted. This model is based on Evolutionary Algorithm (EA). In this model, a new pricing scheme known as day-ahead load shifting, is mathematically used as a minimization problem. In this scheme, the objective load curve is taken as an input to DSM system, the DSM system computes the required load control to avoid the load beyond the consumption limit. The model is simulated for all types of end users including residential, commercial and industrial. Residential load contains 14 different types of household appliance e.g., dryer, washing machine etc., while, total loads in case of commercial and industrial types are 8 (e.g., AC) and 6 (e.g., arc furnace) respectively. The authors show that the waiting time of appliances is inversely proportional to delay. Simulation results show improvement in terms of reduction in PAR and total energy cost. However, the fairness issue is not addressed in the proposed work.

In this paper, we propose an alternative G-DSM model based on GA. The G-DSM model architecture consists of the power flow and bidirectional communication to establish a real time communication environment between power utility and the end users. Each user is equipped with a smart meter and EMCU. Load information is exchanged between these two modules. Non-Delayable Appliances (NDAs) are directly connected with smart meter and the EMCU has no knowledge of power consumption of NDAs. However, EMCU considers the power consumption of NDAs obtained from smart meter to avoid the power capacity limit violation. Figure 1 and 2, show the proposed system architecture for single and multiple users scenarios respectively. Problem formulation is presented in next section.
III. PROBLEM FORMULATION

We consider that scheduling horizon for a user is 24 hours, i.e., a single day. It is needed from user that he/she should provide the information about the particular appliances to be used in a particular day. The user defines the specifications of appliance (e.g., appliance priority, lower time limit $T_L$ and upper time limit $T_U$ of appliance operation, and length $\ell_{dai}$ of operation cycle) through the appliance user interface. The scheduling horizon (i.e., time frames) can be represented as:

$$t_s \in T \triangleq \{1, 2, \ldots, T\},$$  

where, $T = 24$ for a single day. For a single user, the set of household appliances is a combination of Delayable Appliance (DAs) and Non DA (NDAs).

$$\text{TotalHouseholdAppliances} \triangleq \{DAs + NDAs\},$$  

The set of DAs contains Timed Appliances (TAs) and Regular Appliances (RAs). TAs are those appliances which have a specific deadline for completion of their operation. This deadline is defined by the user according to their requirements, at start of the scheduling horizon. Whereas, RAs are those appliances which have an internal control system (e.g., thermostat) to control their operation. The set of DAs can be represented as:

$$DAs \triangleq \{TAs + RAs\},$$  

where $da$ is any specific delayable appliance from a set of $DAs$, and $n$ represent the total number of delayable appliances.

The total power required for each $da$ to complete its operation is,

$$P_{da} \triangleq \{P_{da1}, P_{da2}, \ldots, P_{dan}\},$$  

and the per unit time (hour) power consumption of each $da$ is given as,

$$X_{da} \triangleq \{x_{da1}, x_{da2}, \ldots, x_{dan}\}.$$  

Now, we will define a variable vector of starting time frames of $da$ within $T_L$ and $T_U$,

$$t_s \triangleq \{t_{s1}, t_{s2}, \ldots, t_{sn}\},$$  

and constraint equations can be written as

$$t_s \in [T_L, LST],$$  

or

$$T_L \leq t_s \leq LST,$$

where, $LST$ is the Latest Start Time for TAs from which the operation of TAs must be started and can be obtained by subtracting the length of appliance operation from their upper time limit ($T_U$) and is given as,

$$LST = T_U - \ell_{dai}. $$

The number of appliances and their specifications used for simulation purposes are taken from [14] and [15] as shown in Table I, II, and III. In next subsections, the mathematical formulation of billing mechanism as well as individual objective functions are investigated.
A. Billing Mechanism

We consider a dynamic billing mechanism for implementation of the proposed model. The RTP data for 60 days (from 1st January 2014 to 1st March 2014) is obtained from Illinois power company for zone 1 [13]. The RTP data on a single day, i.e., March 10, 2014 at different hours is shown in Figure 3. The lowest price can be seen at the 3rd hour (3 am). The two peaks occur at 7th (7 am) and 20th hour (8 pm). The most critical issue with RTP is load synchronization; the phenomenon of high load accumulation just after the peak hour price finishes. To avoid the problem of load synchronization and to enhance the stability of electrical power grids, we adopt two criteria to assure power capacity limit. First one is the IBR, as given below:

\[ C_{(t_s)}(x_{(t_s)}) = \begin{cases} C_{(t_s)}^{(1)}, & \text{if } 0 \leq x_{(t_s)} \leq x_{th}, \\ C_{(t_s)}^{(2)}, & \text{if } x_{(t_s)} > x_{th}, \end{cases} \]  

(11)

where, \( x_{(t_s)} \) is the total power consumption at time frame \( t_s \) and \( x_{th} \) is the power consumption threshold limit. Whereas, \( C_{(t_s)}^{(1)} \) and \( C_{(t_s)}^{(2)} \) are two different price values and \( C_{(t_s)}^{(1)} \) must always be less than \( C_{(t_s)}^{(2)} \). The second criterion is the total power consumption capacity limit for a predefined billing period. For example, the two-step conservation rate model followed by Hydro, et al [16]. The graphical representation of this model is presented in Figure 4. According to this model, for the first 1,350 kWhr, the residential users pay 7.52 cents per kWhr, they use over an average two-month billing period. After crossing the power consumption capacity limit, the users must pay 11.27 cents per kWhr.

The effect of the power consumption capacity limit combined with an RTP data on a single day is shown in Figure 5. The price varies for each hour according to the real time load scenario from the end user. When load exceeds the threshold at lower prices, the EMCU delay the loads according to their characteristic and priorities.

B. Energy Cost Minimization

The optimization problem for cost minimization can be written as:
The total power capacity limit defined by the power distribution utility for each user for a specified billing period. \( WTA_{da} \), is the appliance delay time at \( t_s \) and \( WTA_{da(max)} \) is the maximum allowable delay of each appliance specified by the user, while \( t_s \) is bounded by \( T_L \) and \( LST \).

\[ \min \text{Cost}(t_s) = \sum_{n=1}^{N} \sum_{t_s=1}^{T} \sum_{da \in DA} (X_{da}^{(t_s)})_n C_{t_s}, \]  

subject to \( \sum_{da \in DA} X_{da}^{(t_s)} \leq P_{CL}, \) 

\( WTA_{da} \leq WTA_{da(max)}, \) 

\( t_s \in [T_L, LST]. \)  

In Eq. (12), \( X_{da}^{(t_s)} \) is the power consumption of all \( da \), \( C_{t_s} \) is the electricity cost at any specific time frame \( t_s \), and \( N \) is the total number of users (i.e., \( N=20 \)). The \( P_{CL} \) in Eq.(13), is the total power capacity limit defined by the power distribution utility for each user for a specified billing period. \( WTA_{da} \), is the appliance delay time at \( t_s \) and \( WTA_{da(max)} \) is the maximum allowable delay of each appliance specified by the user, while \( t_s \) is bounded by \( T_L \) and \( LST \).

### C. PAR Reduction

The total power consumption of a single appliance at different time slots can be defined as:

\[ X_{Load(da)} = \sum_{t_s=1}^{T} X_{da}^{(t_s)}, \]  

The daily power consumption of a single user for all time slots can be written as:

\[ X_{Load} = \sum_{t_s=1}^{T} \sum_{da \in DA} X_{da}^{(t_s)}, \]  

For a single user, PAR can be calculated from the maximum and average power consumption at a specific time frame, and can be written as,

\[ PAR = \frac{\max(X_{Load})}{\text{avg}(X_{Load})}, \]  

Therefore, for multiple users, the PAR becomes,

\[ \min \frac{\sum_{n=1}^{N} \max(X_{Load})}{\frac{1}{T} \sum_{s=1}^{N} (X_{Load})}. \]  

### D. Reducing WTA

The user’s comfort is dependent upon WTA and energy cost. Therefore, trade off is necessary between WTA and energy cost. The mathematical formulation of WTA for TAs can be written as:

\[ WTA_{da} = \frac{t_s - T_L}{LST - T_L}, \]  

\[ \min \ WTA_{da} = \sum_{t_s=1}^{T} WTA_{da}^{(t_s)} x_{da}^{(t_s)}, \]  

subject to \( WTA_{da} \leq WTA_{da(max)} \), \( \forall da \in DA \), 

\( t_s \in [T_L, LST]. \)  

In Eq. (19), the value of WTA is calculated for each appliance in all time slots according to the power consumption of each appliance, whereas constraints are represented in Eq. (20). The value of \( WTA_{da} \), at any specific time frame can be found as:

\[ WTA_{da} = \begin{cases} 0, & \text{if } t_s = T_L, \\ \frac{T_s - T_L}{LST - T_L}, & \text{if } T_L \leq t_s \leq LST, \\ 1, & \text{if } t_s = LST. \end{cases} \]  

The pictorial representation of (21) is given in Figure 6.

### E. GA Based EMCU Model

GA based optimization is adopted to find the optimal value of power consumption in scheduling time frame. GA simulates the appliances’ scheduling process in natural manner necessary for evolution. GA is started with a set of randomly initialized population as shown in Figure 7. After evaluation of the objective function including minimization of cost, PAR and WTA, individuals are selected in pairs to perform the crossover operation. According to the flowchart, the crossover is performed for
all individuals. After crossover, offsprings are selected and mutated for finding the best fitness function. As a result of mutation process, the best individual (i.e., chromosome) is selected at each iteration. The process is repeated iteratively and fitness values are calculated and compared until a satisfactory result is obtained. The crossover and mutation probabilities are set to 96% and 1% respectively. The type of mutation is uniform. The termination criterion is the 500 generations in our model. Population size used for GA operators are 200 and the selection method used for individuals is Roulette Wheel. All these parameters are shown in Table IV.

As shown in algorithm 1, after initializing \(t_s\) for each \(da\) while respecting the peak hours, the second phase is the calculation of total power consumption at each \(t_s\). If the total power consumption at any particular time slot violates the power capacity limit, the lower priority appliances are shifted to later time slots. The process continues until the power capacity limit of all time slots is met. Using GA, fitness function are calculated for all time slots and the best fitness function is selected. In case of multiple users, each individual user broadcasts their power consumption information to other users.

Algorithm 1 Scheduling Algorithm For EMCU.

1: Initialize parameters \((DAs, l_{da}, T_L\) and \(T_U)\)
2: for all \(da \in DA\) do
3: select \(t_{si}\) for all scheduling appliances
4: if RTP is high (peak hours) then
5: Delay \(da\)
6: else
7: start an appliance
8: calculate \(P_{Total}\)
9: end if
10: for all \(da \in DA\) do
11: if \(P_{dai(t_s)} > P_{CL}\) then
12: shift all low priority appliances
13: until
14: \(P_{dai(t_s)} < P_{Total}\)
15: end if
16: for all \(da \in DA\) do
17: calculate fitness using GA do
18: if \(N_{gmax} = N_g\) then
19: select
20: best fitness function
21: else
22: repeat whole process
23: until \(N_{gmax} \leq N_g\)
24: broadcast info. with other users
25: end if

IV. RESULTS AND DISCUSSIONS

In this section, we discuss the energy cost minimization, PAR reduction, relationship between \(WTA_{da}\) and electricity cost obtained by applying the proposed EMCU based model. Figure 8 shows the electricity cost minimization of a single user after applying GA. The average electricity cost is reduced from 41.53 cents to 25.17 cents. The percentage reduction in average electricity cost of a single user is about 39.39%. Accordingly, the PAR reduction in case of a single user is shown in Figure 9. The average PAR value is 6.64, which is reduced to 5.50 after applying the GA based proposed EMCU based model. The percentage reduction in PAR of a single user is 17.17%. The effect of NDAs on energy cost and PAR on a single user as well as on multiple users will be discussed in subsections A, B and C.

Table IV. Parameters used for G-DSM model simulation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population Size</td>
<td>200</td>
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<tr>
<td>Selection</td>
<td>Roulette Wheel</td>
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<tr>
<td>Elite Count</td>
<td>2</td>
</tr>
<tr>
<td>Mutation</td>
<td>Uniform (0.01)</td>
</tr>
<tr>
<td>Crossover</td>
<td>0.96</td>
</tr>
<tr>
<td>Stoping Criteria</td>
<td>Generations (500)</td>
</tr>
<tr>
<td>(x_{th})</td>
<td>1.35 kW</td>
</tr>
<tr>
<td>(P_{CL})</td>
<td>1350 kW</td>
</tr>
</tbody>
</table>

Figure 8. Average Daily Electricity Cost Minimization of a Single User.

A. Impact of Multiple Users

The proposed GA based appliance power consumption scheduling algorithm is applied for 20 users, having different power consumption profiles. The proposed EMCU based model is still effective by reducing each user individual electricity cost as well as mitigating the peaks generated by these users. Figure 10 shows the reduction of PAR to 3.19 from 6.68 after managing the loads through EMCU. The percentage reduction in average PAR is 52.24%. Similarly, the average monthly electricity
cost in dollars for 20 users is 4.82 and 2.61, before and after applying the proposed EMCU respectively. The percentage reduction is about 45.85%, as shown in Figure 11.

**B. Impact of NDAs**

The behavior of the proposed EMCU is demonstrated in Figure 12 and 13. In Figure 12, there is a considerable reduction in monthly electricity cost for each user, however, when the number of NDAs increases, the performance of EMCU degrades because of the undelayable nature of NDAs. Figure 13 shows the effectiveness of the EMCU by considering both DAs and NDAs collectively. Average daily electricity cost is plotted against the 60 days scheduling period. In this simulation, 15
NDAs along with 8 DAs are considered. The combined electricity cost in cents on daily basis is reduced from 46.53 to 34.61, which is approximately equal to 25.62% reduction. The combined effect of adopting EMCU for both types of loads is shown in Figure 14. The results demonstrate that by increasing the number of NDAs, the gap between the obtained curves without EMCU and with EMCU gets wider. It can be concluded that despite allowing NDAs up to some definable range, the proposed model gives satisfactory results.

**C. Relationship between Electricity Cost and WTA**

WTA is one of the most important aspects of energy consumption scheduling techniques. The user comfort is inversely related with WTA. Therefore, load categorization is performed before applying the proposed EMCU based model. All those appliances which are the most crucial for user comfort and have no delay tolerance, are categorized as NDAs. Most of NDAs have low power consumption and so they have little effect on the total power consumption of a user if kept in some definable range. All other appliances are categorized as DAs. There are two types of DAs; TA and RA. For each TA, user provides the input about $T_L$, $T_U$, and $l_{da}$. The EMCU calculates WTA for each TA and optimizes the scheduling time of appliance between these limits to complete its operation. When control system of RA initiates appliance starting signal, the EMCU checks power consumption of that specific appliance. If the total power consumption does not violate power capacity
limit, the EMCU starts an appliance. Otherwise, the appliance operation is scheduled according to the priority defined by the user. Appliance having lower priority may be delayed more as compared to those appliances which have higher priority. The proposed EMCU based model ensures trade off, between the user electricity cost and the WTA. Figure 15 shows the trade off region between electricity cost and WTAa.

V. CONCLUSION

In this paper, we developed a new G-DSM model based on EMCU. The GA algorithm finds out the optimal schedule of each appliance for EMCU by selecting the suitable starting time for each appliance respecting the RTP and power capacity constraints. G-DSM performance is evaluated and compared for different loads with load management through EMCU and without load management. The simulation results show that the proposed G-DSM model minimizes the individual user cost by 39.39% and 20 users cost by 45.85%. The reduction in PAR for single and 20 users are 17.17% and 45.24% respectively. By adopting 8 NDAs, the cost reduction in cents on daily basis is 25.62%. The relationship of WTAa with electricity cost is also demonstrated. We observed that the proposed G-DSM model is more flexible in terms of ‘number of users’ and ‘number of appliances’.

REFERENCES