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***Abstract*— Current power generation and distribution systems are designed for minimal peak-to-average ratio (PAR) demand, with any fluctuations leading to the addition of alternative, more expensive power generation and a significant increase in pricing for the consumers. While prior research proposed a number of solutions to reduce PAR, the issue remains topical due to the challenges in reallocating demand in a more efficient way. This paper proposes a novel Demand Side Management (DSM) which focuses on a community-based allocation of power demand for minimising the peak load. In the proposed environment, users minimise the peak-to-average ratio (PAR) of the power system by shifting consumption to off-peak times, but the policy is more effective due to the community-based nature of the demand. A daily real load profile of a user was applied to measure the performance of the proposed scheduling technique when minimising PAR, with preliminary experiments demonstrating that the method is able to successfully reduce PAR and peak load.**

Keywords- demand-side management; load scheduling; peak-to-average ratio; Energy consumption scheduling

I. Introduction

Typical energy consumption for a household introduces two peak times over the course of the day. Biological disposition affects rates of metabolism and energy levels over a 24-hour cycle. Most people sleep at night and awake during the day. External institutions such as employers, school and church demand people's presence at particular times of a day. As a result, if working adults watch television, they are especially likely to do it during the prime-time hours of *8.00–10.00 p.m* and so on [1].Therefore, these consumption patterns might lead to daily peak load. Studies in the United States, the Netherlands and the UK have estimated that 26–36% of in-home energy use is due to residents behaviour [2]. In order to respond to the resulting in demand during these periods, energy providers rely on more expensive power sources which, in turn lead to more expensive energy costs for customers. Due to the price of generated power increasing with variability of the demand, overall price of energy to the consumer over the course of the day is proportional to the ratio between peak load and average consumption, (PAR) [3]-[5]. Instead of traditional power girds, smart community that composes of Smart Grid (SG), smart homes, and home energy management programs could be utilised to reduce the daily peak loads [6]. Smart Grid (SG) offers the eco-friendly intelligent power grid for efficient generation, distribution, and consumption of electric energy [7]. At the core of the smart grid is the smart home, which describes the automation of connectivity and control of various appliances in the house in one place [8], [9]. In this context, home energy management programs, which are responsible for controlling of individual appliances properties, have received significant attention in recent years. This management provides important features of energy consumption such as cost, and comfort. This management is considering to be a primary unit of power consumption management in one community in order to reduce the aggregated daily peak load. Home energy management programs focus on either reducing consumption or shifting consumption [10], [11]. The former can be implemented through raising awareness among subscribers for more careful consumption patterns as well as constructing more energy efficient buildings. The latter is necessary to address the variable demand by transferring load from on-peak to off-peak times.

Demand Side Management (DSM) is the encompassing area for controlling and managing energy consumption in the demand side for minimising the peak load and fluctuation. As part of DSM, prior research highlighted, Home Energy Management (HEMS), and Demand Response (DR) as integral components. DSM is the general category that refers to the methods that influence the energy consumptions of end users. As the demand for electricity varies between consumers, DSM focuses on habits of users [12], [13]. HEMS provides monitoring and control service with the usage of electricity for each household through sensors and/or controllers connected to the appliances [12], [13]. DR is defined as incentives introduced to electricity users on reducing their power consumption in response to an energy provider's need for electricity due to a high system demand for electricity or emergencies that could affect the transmission grid [12]. Further, DR can be also defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised [14], [13]. These solutions will bring benefits to energy providers, households and the environment. For providers, it can reduce peak load conditions and increase the supply reliability. For households, it can reduce the energy use during peak times and hence provide financial savings, increase awareness of energy information and help households minimise energy wastage during off-peak times. For the environment, it can save a significant amount of CO2

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emission through using more energy from green or low carbon sources. As such, it could be considered to be one of the most cost-effective measures, so far, to address the issues of environment, households, and energy suppliers [15]. A number of studies focused on reducing the PAR by proposing new controlling and scheduling methods for households appliances [3]-[5], [10]. Nevertheless, there are still a number of issues to solve including optimising power consumption via one particular community, appliance-by-appliance controlling, using real data set for evaluation.

The primary objective of this research is to reschedule the power consumption of one household taking into consideration the surrounding community consumption patterns. This paper proposes a new DSM to reduce PAR and decrease the load demand fluctuation. This method will also base on appliance-by-appliance scheduling as recommended by [16]. Therefore, the proposed DSM will require further modifications in Home Energy Management Systems (HEMS) to enable to control individual appliances. The proposed DSM system, in turn, would enable continuous minimising of PAR, taking into account a group of households in one community. The proposed method for power consumption management will be based on rescheduling the appliances' operation times.

II. RELATED WORK

Minimising the Peak-to-Average ratio has received significant attention in the research community due to the nature of the on-demand variable generation [17], [18]. Furthermore, assuming that the overall power consumption remains constant, PAR reduction would lead to a significant peak reduction. As a result, increasing the reliability of energy providers during peak demand periods. Power generation and power distribution are in dangers beyond a certain PAR. While these high PAR levels were the main factors of Californian electricity crises of 2000 [17], [19]. A number of studies have utilised DSM for PAR reduction. [10] Applied a new DSM architecture that scheduled appliances to reduce PAR using an Energy Consumption Scheduler (ECS). ECS is functions or additional capabilities assumed to be installed for the individual user at the smart meter and connected to network communication by LAN and power line. ECS can control intelligent appliances and interact with an external party. [20] Considered energy storage devices which are reasonable in the future smart grid beside the domestic appliances. The scheduling concept was implemented for charging and discharging the storage devices in a more efficient manner, and the resulting PAR of this DSM's evaluation was reduced from 1.8 to 1.3. However, without charging and discharging cycle's scheduler of the storage devices, it is possible for all end-users with storage devices to try charging their devices at the same time when the energy cost is low. This will result in high peak load in unexpected time. [3] Attempted to overcome this issue by integrating the Energy Scheduler (ES) with DSM for the success the goal of DSM system, using the Dispatchable distribution Generation (DG), storage devices, and Renewable Energy Sources (RESs) for controlling the peak load. In [21]-[23] the authors focused on HEMS for PAR reduction. [21] developed a scheduling operation model of domestic electric appliances using Mixed Integer Linear Programming (MILP). [22] Presented an appliance commitment algorithm that schedules Thermostatically Controlled Appliances (TCAs). A similar but more complex power consumption study was conducted by [23] who enabled automatic power control. In this automatic power control, the appliances are turned on and off without human action according to their control parameters. They implemented the lighting dimming by integrating Digital Addressable Lighting Interface (DALI) protocol in the developed Wireless Sensor Network (WSN).

From a different perspective, DR is a class of DSM programs in which distribution companies offer incentives to households in order to reduce their consumption during peak hours. [24] Presented a new strategy of pricing between users and providers that considered the difference between the nominal demand and the actual consumption based on the Time-of-Use (TOU). TOU is one of DR programs that give different price rates. These rates are electricity prices per unit consumption that differ in different blocks of time per day. [25] Proposed a scheduling unit to achieve home automation systems, which distinguishes the interruptible and uninterruptible residential load, avoids concentration of all appliances on low price hours, and changes provided power to multiple retailers of electricity. As a result, it reduced PAR by 38% in a single user scenario, and by 22% in a multiple users' scenario. [26] Presented a new DR management that integrated Plug-in electrical vehicle and distributed generators. They applied Alternating Direction Methodology of Multipliers (ADMM) to solve the peak problem formulation. ADMM is an algorithm that solves convex optimisation problems by breaking them into smaller pieces.

There is only one study [27] who proposed increasing the community interaction among households by sharing individual usage and scheduling the appliances working times based on other community members. As such, a move towards increasing the power consumption interaction among households in one community. The PAR could be reduced by one community households as examined by [25], who pointed out that increasing the number of users can further balance the aggregated load. While most studies reschedule the operation times of power consumption of households, some of them focus on appliance-by-appliance scheduling, as recommended by [16], given it is more practical and easy to map on a real environment. Nevertheless, this might require more effort for the collecting load data and more complex power management algorithms [28]. With respect to performance, many studies never performed a real data for the evaluation. Merely synthetic data is used [3], [29]; however, the importance of the real data is emphasised by the research community [21], [16]. In addition, the applied random household load profiles were significantly variant, therefore the proposed solutions are not comparable. For example, the PAR of the load profile of household before implementing the proposed solutions applied by [25], and [20] were 4.49 and 1.8 respectively. At the same time, [20] reduced the PAR only by 0.2 from 1.8 to 1.6. Therefore, it would be ideal to conduct an extensible evaluation, having actual participant data in order to have a more accurate insight into the system. However, although the methods of PAR minimisation were demonstrated, little attention has been paid to utilise community aspects and appliance-by-appliance in order to reduce PAR. In addition, little focusing has been shown on applying a real load data to evaluate the proposed systems of PAR reduction.

III. Proposed System

The proposed architecture consists mainly of two types of components as in Figure 1: the household domain component and the community domain component. These entities are responsible for collecting the load profile from users, analysing these data, imposing usage policies, and controlling the appliances' operation times based on these decisions. The proposed architecture begins with collecting data. This step consists of appliances connected to a controller responsible for connecting to the smart gateway in each house. In order to achieve this communication among appliances, controllers, and the gateway, there are several communication protocols such as KNX, EIB, and EQ3/Bidcos. It is assumed that the gateway will resend the predetermined load profiles of the households to the community domain server that include intended appliances operational times, in addition to real-time load profiles. This server is provided with a super computer to implement the novel scheduling algorithm. The process is followed by matching the obtained PAR with the desired PAR value that was determined by providers or based on user preferences. The last step of the proposed architecture process sends the decisions of the new load demand back to the users. Moving from single users to a group of users is likely to improve the power consumption in two ways. First of all, appliances shifting is not individual. The members of the group take turns shifting appliances and using appliances. The second is that different members of the group may have slightly different peak and off-peak periods. In addition, the last point would add more flexibility for the scheduling. Figure 1 provides an outline of the proposed system. The architecture has two main domains: the users domain and the community domain. The core component of the users domain is a consumer gateway, which collects consumption by each appliance and controls the shiftable appliances. The gateway may also collect user preferences, such as the required parameters to trade between cost reduction and convenience. Communication protocols are used to overcome the interaction among these entities, such as JSON or XML. In turn, each gateway is connected to the local community server that aggregates and schedules consumption. First of all, grouping the households based on their load profiles and preferences will apply. After the households grouping step, applying a new scheduling schema which is community-based will be implemented. In this schema, implementing resource sharing concepts will consider for example cloud community [30] and Cooperative consumption (CC) [31], [32]. CC will be adopted in the new scheduling schema to consider the power as a resource to share among households. In CC, there is schema called "use rather than own" which will be implemented by several strategies such as car sharing methods [33] and Customer-to-Customer (C2C) interactions[34]. In terms of the novelty of the proposed method, off-peak times will be used rather than own and resource sharing among users will be applied to spread the power usage throughout the community.

The results and analysis in this paper differ from the related work in the literature by considering several aspects, as follows: A community-based solution in which reschedule the power consumption of one household taking into consideration the surrounding community consumption patterns. Appliance-by-appliance scheduling is a bottom-up model that can be easily applied to develop new control algorithms and disaggregation of the electric consumption[23]. Real load profiles data of households lead to valuable performance evaluation of the proposed system and easily map it to real environment, etc. In order to understand the presented schema, the scenario of the proposed architecture is described. At first, it is started by obtaining the predetermined load profile from the users. Then based on a historical data of load consumption profiles of the users, the daily peak and off-peak load is determined in order to turn on the shiftable appliances outside of peak times. The obtaining of the predetermined load process begins by turning on all the daily required appliances in households. This is the only required input entered by the users.

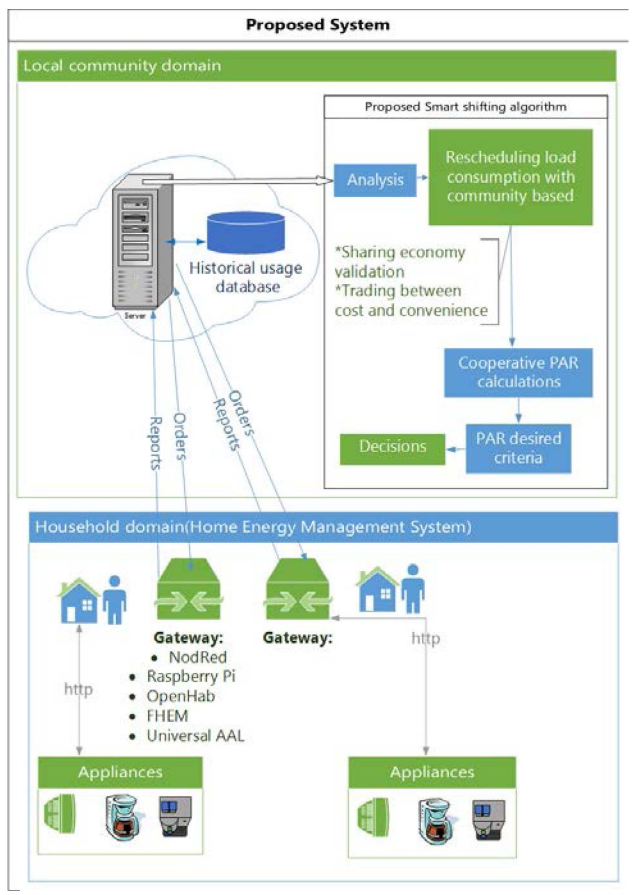

Figure 1. Proposed system for DSM based on community interaction.

Next, the individual gateway of each household takes the responsibility for collecting all the power load data of the appliances in each house. It is noteworthy that all the types of appliances even the traditional appliances (not smart) are able to send the power data and to receive the control signals to and from the gateway using a wireless smart plugin devices. The gateway is responsible for sending the collected power data as a report to a local community domain server. After the local community domain server collecting all predetermined households power data, this server starts reshaping the intended power usage of households. This reshaping process requires a prediction of the daily on-peak and off-peak times which can be found based on the historical power consumption profiles of the households that are stored in a database storage. Furthermore, the reshaping process needs to analyse the current collected predetermined power data to group the intended consumption into shiftable and non-shiftable power consumption. Then turn off the shiftable appliances at on-peak times and turn them on at the off-peak times that were previously determined using the historical data. Turning the shiftable appliances on/off is based on a basic programmed algorithm that runs on the local community server. These operation periods of all appliances result from the algorithm sending back to the gateway of each household as orders or decisions in the purpose of PAR reduction. The gateway of each household is responsible for passing these new operation periods to each individual appliance. A primary algorithm has been applied to reduce PAR. The goal of this algorithm was to reshape the household load profile by rescheduling the shiftable appliances from on-peak to off-peak hours. Scheduling technique is used by [3], [10], [16], [17],[20]; here, some adjustments were suggested suitably for scheduling the load by power consumption management. As a result, peak load was decreased and the demand stability was increased. The process flow of the rescheduling load process started with analysing the load profile of the user and specifying the on peak and off peak times. Then it followed by shifting procedure for shiftable appliances to decrease the peak load demand. The last step is to update the user with the new load demand. The comparison evaluation of the algorithm-base load to the original load was applied by compute peak load, and PAR.

IV. EXPERIMENT (METHODOLOGY)

This experiment considers a smart power system consisting of single energy provider and a single user. The power consumption of this user is based on a previous investigation involved 250 real households load profiles across England from 2010 to 2011. In this investigation, the households' appliances were monitored over 24 hours at an appliance level with a granularity of 10-minute intervals [30]. 144 meter readings associated with 10minute timeslots for each appliance were analysed and rescheduled based on an algorithm implemented in R, as aforementioned described in proposed system section.

A. System Formulation and the Evaluation Metrics

In this experiment, n is supposed to equal one user, this user equipped with a number of appliances and is denoted by M_n a number of appliances for user n. S_n,I_n are denoted list of names for shiftable appliances and essential appliances (non-shiftable appliances) for user n respectively. The intended time of operation is divided into $T = 144$ 10-minute slots. In each time slot, there is one meter reading of all household's appliances each 10 minutes for one day. Then, the energy consumption scheduling vectors for S_n,I_n are $x_{n,s}$, $x_{n,i}$ for shiftable and non-shiftable appliances respectively. The following equation is used to compute the l_n^t for load demand of n user at slot time t:

$$l_n^t \triangleq \sum_{i,s\in M} x_{n,i}^t + x_{n,s}^t \tag{1}$$

And the total daily load L_h of n user can be found as below:

$$L_h \triangleq \sum l_n^t \tag{2}$$

The beginning and ending of daily operation time for shiftable appliances are $\alpha_{n,s} \in T$, $\beta_{n,s} \in T$, while the maximum and minimum power for each appliance are, $x_{n,m}^t \geq \gamma_{n,m}^{min}$. Based on the above notation, PAR can be formulated in terms of load demand for number of users as follows [11], [20]:

$$PAR = \frac{\max_{t\in T} \sum l_i^t}{\frac{1}{T}\sum Li} \tag{3}$$

And the PAR minimisation problem can be formulated to find out the minimum possible value of the maximum daily load as follows:

$$\min_{xi,\forall i} \quad \max_{t\in T} \sum l_i^t \tag{4}$$

V. RESULTS AND DISCUSSION

The impact of the proposed method was evaluated by comparing the load demand following the application of the shiftable management, with the original load demand for the same household with power loads. Fig. 2 shows the results obtained using the power consumption management. It can be concluded from this figure that PAR of the algorithm-based load was appreciably lower than PAR of the original load; where the PARs of both loads were 1.4 and 1.5 for the algorithm-based load and original load respectively. It is evident that the PAR results obtained here are exceptionally good agreeing with existing PAR results of [20] and [11] which were minimised from 1.8325 to 1.8315 and 1.8 to 1.6 respectively. The peak load is interestingly decreased from 725.5W at 6:10 pm to 671.1W at 6 pm. As can be seen, during both daily peak time periods the algorithm-based load demand of the household was significantly less than original load demand, which is consistent with the results obtained in previous study [21]. However, the algorithm-based load demand in this study was not consistent with a number of studies [25], [11], [16], [20], [24],[17], [3], [29] who used merely random load or who adopted additional energy storage devices such as battery, renewable energy resources, and Distributed Generators [20], [3], [26]. It can be seen that the first hours of the day from 00:00 to 06:00 am, the algorithm-based load resulted in a considerably higher level than the original load; however, in this period the energy is easier and cheaper to produce, which is an advantage for both power companies and users.

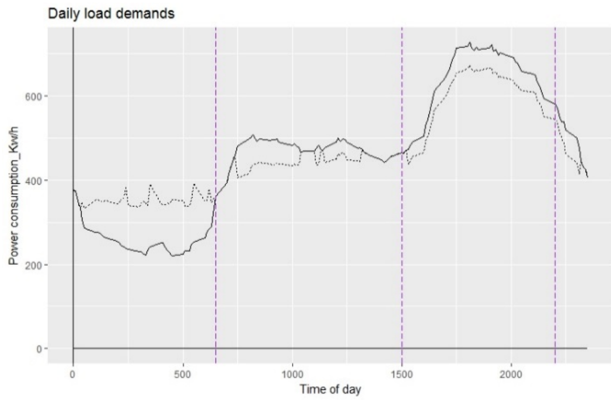

Figure 2. Power consumption for (a-solid line) original household demand and (b-dotted line) proposed DSM algorithm.

During the second period of the day from 06:00 am to 4:30 pm, the algorithm-based load was significantly less than the original load; as a result, the benefits for users and providers are applied. Where, providers have a match between supply and demand. During the last part of the day from 04:30 pm to 23:00 pm which is the most problematic period for both users and providers. In other words, at peak times users pay twice the off-peak times, while providers always have issues for the supply and dispatch demand. The algorithm-based load was advantageous comparing with an original load.

VI. CONCLUSION AND FUTURE WORKS

This paper proposes a DSM algorithm using community-based approach for efficient energy utilisation. Prior work has documented the effectiveness of Demand Side Management (DSM) in improving power consumption and reducing Peak-to-Average Ratio (PAR). However, these studies have either been not considering community aspects or have not analysed a real user load profile. The algorithm is analysed using a real load profile in order to measure the PAR, and peak load. The evaluation results indicate that PAR is reduced for the load profile from 1.5 to 1.4. As a next step, future research will focus on the willingness of users to a trade-off between convenience and cost, leading to a potential higher acceptance of the proposed system. Once a robust algorithm is designed to include user motivation elements, as part of community-based usage a real-time implementation of the proposed system could be utilised to measure the applicability of the proposed system.

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