Demand Based Cost Optimization of Electric Bills for Household Users

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Abstract- Internet of Things (IoT) is increasingly becoming the vehicle to automate, optimize and enhance the performance of systems in the energy, environment, and health sectors. In this paper, we use Wi-Fi wrapped sensors to provide online and in real time the current energy consumptions at a device level, in a manner to allow for automatic control of peak power consumption at a household, factory level, and eventually at a region level, where a region can be defined as an area supported by a distinct energy source. This allows to decrease the bill by avoiding the usage of heavily and controllable loads during high tariff tier and/or peak period per household and to optimize the energy production and distribution in a given region. The proposed model relies on adaptive learning techniques to help adjust the current load, while taking into consideration the actual and real need of the consumer. The experiments used in this study makes use of current and voltage sensors, Arduino platform, and simulation system. The main performance indexes used are the control of a peak consumption level, and the minimum time needed to adjust the distribution of load in the system. The system was able to keep the maximum load at a maximum of 10 kW in less than 10 seconds of response time. The level and response time are controllable parameters.

***Keywords*:** Demand Side Management, Internet of Things, Smart Grid.

1. Introduction

According to US Energy Information Administration (EIA), the cost of energy continues to grow despite the continued and increased use of cheap and renewable energy sources [1].To meet the challenge of growing cost, it is incumbent to investigate the means of lowering, controlling or optimizing the demand for electricity energy at residential, commercial and industrial customer sites [2]. A report released by the International Energy Agency (IEA) finds that in 2018 global energy demand grew by 2.3%, the fastest pace in a decade, leading to 1.7% of growth in energy-related CO2 emissions. This is despite the fact that renewable energy sources in meeting new energy demand keeps growing and energy efficiency continues to increase. It is noted that the rates of improvement are far below those required to meet the challenges of growing demand [3]. In this paper, we address a key solution to the challenge of growing demand, which lies in the necessity to manage the demand rather than to produce more energy and seek new sources, which evidently cause disruption in the climate management, and lead to consequences far more than the increasing energy bill.

Demand side Management (DSM) generally aims to make the demand for electricity more flexible, where it can be forecasted and controlled to match the supply [4]. Given the uncontrolled culture of the tendency to use electric energy as long as it is available and useful. Even the attempt to control the ongoing usage of electric power is mostly done in an irregular, uninformed basis, such as turning off lights, using more efficient AC units, and so on. Evidently, this type of behavior is not based on a well-defined calculation of the energy usage at a given point in time. Studies similar to the one in [5] and [6] discuss scheduling algorithms which are dedicated for thermal loads and for HVAC systems only.

Heuristic approaches such as GAs (Genetic Algorithms) have also been used to optimize domestic consumption to yield cost reductions where it can adapt to load variations [7]. The work presented in [8] has used a heuristic approach for active demand management for an off-grid system consisting of renewable sources (PV and Wind). The aim of the system was to control power consumption according to the prevailing weather conditions. The system was an actual system built in the Technical University of Ostrava's campus, Czech Republic. There, they managed to control energy flow and increase the efficiency of renewable energy systems, harnessing the roles artificial intelligence methods can play, in both of the underlying software and hardware parts. Authors of the work in [9, 10] presented another management system based on heuristic methods where home energy models were simulated in a real time pricing environment and were shown to yield energy cost minimization. The study showed that BPSO worked better towards cost reduction. Today, with the advancement made in the area of Internet of Things (IoT) technologies, it can be noted that IoT can be utilized to manage domestic power consumption just as well. Internet of Things (IoT) offers a space of interconnected items that are capable of rendering remote as well as near-end services as it can provide information about different devices simultaneously. It also benefits from available sensors and the pervasive wireless communication infrastructure [11].

The shift to smart grid is critical to satisfy real power demand and match supply with demand. Also, it facilitates the provisioning of electricity from different suppliers creating a possible trade commodity [12]. The energy sector has a lot to gain from IoTs, especially with the emergence of new energy infrastructures dubbed as the Internet Energy of things (IoET) [13].

This paper proposes a complete practical system that monitors the power consumption of domestic devices in real-time, and controls the operation of these devices remotely. Furthermore, it tests the performance of two scheduling algorithms in a simulated environment. The proposed model in this study relies on the ability to recognize plugged in devices based on a unique characterization of the device, which could act as a fingerprint of the device.

In the next section, we provide a survey of relevant work. The Model and the proposed algorithms are presented in section 3; section 4 presents the simulation results, and finally conclusions are presented in section 5.

2. Related Work

Tawalbeh et. al. [10] presented a model for demand based optimization of electric power consumption using Binary Particle Swarm Optimization (BPSO) [14]. The researchers showed the current load of a household electric devices can be optimized using the BPSO algorithm. The proposed system in [10] succeeded in maintaining 2000-Watt level (for the controlled devices only) with less than 10 seconds sampling rates, at different control levels pursuant with the type of domestic device used. The built system managed to serve as a monitoring and control device, using the WiFi communication capabilities. The researchers suggested the development of more optimization techniques, which take into consideration more conditions and priorities.

The utilization of the power of Internet of Things (IoT) for the optimization of performance and the reduction of cost in many disciplines including energy consumption at the level of a single household or the grid in general has been recognized by several researchers such as in [11, 15]. The authors in [11] recognize that The Internet of Things (IoT) has been recognized as one of the major technological revolutions of this century [16, 17], although the IoT is still in its infancy. According to the authors in [11], IoT will unleash its full potential with the development of smart applications, which can utilize the power of IoT. The current research is one such application.

Scheduling of load at any given time is addressed as a one of the strategies which has commonly leveraged Neural Networks (NN); this was used for DSMs [18]. The study used MATLAB's NN toolbox where the work presented reflected a reduction in the gap between demand and supply resulting from applying an artificially intelligent algorithm that recognizes the consumption patterns using NNs. NNs are also used for forecasting in real time pricing tariffs over smart grids. NNs are used to evaluate the demand depending on various parameters such as oil price, and previous year's consumption [19]. Another prediction of the demand was done by NNs for an off-grid system using 24 hours of past information where the load profile can be predicted via simulations using NNs [20].

Heuristic approaches such as GAs (Genetic Algorithms) have also been used to optimize domestic consumption to yield cost reductions where it can adapt to load variations [7]. The work presented in [8] has used a heuristic approach for active demand management for an off-grid system consisting of renewable sources (PV and Wind). The aim of the system was to control power consumption according to the prevailing weather conditions. The system was an actual system built in the Technical University of Ostrava's campus, Czech Republic. There, they managed to control energy flow and increase the efficiency of renewable energy systems, harnessing the roles artificial intelligence methods can play, in both of the underlying software and hardware parts. Authors of the work in [9, 10] presented another management system based on heuristic methods where home energy models were simulated in a real time pricing environment and were shown to yield energy cost minimization. The study showed that BPSO worked better towards cost reduction. Today, with the advancement made in the area of Internet of Things (IoT) technologies, it can be noted that IoT can be utilized to manage domestic power consumption just as well. Internet of Things (IoT) offers a space of interconnected items that are capable of rendering remote as well as near-end services as it can provide information about different devices simultaneously. It also benefits from available sensors and the pervasive wireless communication infrastructure [11]

The shift to smart grid is critical to facilitate the transition towards low-carbon energy systems and enable the provision of reliable and cost-effective balancing mechanisms to satisfy real power demand and match supply with demand. Also, it facilitates the provisioning of electricity from different suppliers creating a possible trade commodity [12]. The energy sector has a lot to gain from IoTs, especially with the emergence of new energy infrastructures dubbed as the Internet Energy of things (IoET) [13]. In particular, the IoET enables better understanding the power consumption of residential customers and crucially the provision of a well-defined and predictable load profiles for various energy consuming units.

Said El Abdellaoui et. al. [21] addressed the use of wireless sensor network for the management of energy harvesting. In their research, the authors proposed an algorithm in order to maximize the network lifetime for the energy harvesting system. The results presented in [21] showed that the algorithm OPA-RB achieved a much higher Lifetime than the others algorithm. They propose to address in the future work the application of the algorithm to a multi-hop model using a Non-Orthogonal Multiple Access Systems (NOMAS) with Partial Channel Information (PCI). Different simulation-based algorithms have been also proposed in the literature to reduce peak demand in power grids by controlling residential appliances. For instance, direct load control method is adopted in [22, 23] to connect or disconnect a specific type of load to mitigate congestions in power distribution networks. Also, optimization-based energy management algorithms have been provided, for instance the study in [24] to optimally define the best control actions of controllable loads in response to dynamic price signals. Although the proposed algorithms are found effective to manage power consumption, they have not been implemented and tested in practice. This is important to better understand the implications and challenges of IoET and inform energy policy makers.

In this paper, we utilize the wireless sensor network for scheduling electric devices usage in a household in a manner to manage the energy bill in a given time period.

3. The model and load optimization Algorithm

Figure 1 shows the general model of the proposed system. Ui stands for electric unit (i), Si stands for smart socket (i). Each smart socket is enabled with a wireless connection to a smart and adaptive demand control system (SACS). The wireless connection can be made via Bluetooth Zigbee Protocol (BZP) or WiFi 2.5 or 5 GHz, depending on the size of the facility. In a relatively small home, BZP can be sufficient, whereas in a larger facility such as a factory or an organization, a wider Wireless connection range is required. The SACS unit is responsible for recognizing the plugged in device, its expected power consumption, expected time usage, and to permit the entrance of the unit to the system or to block it based on the deployed algorithm (to be defined in the next section).

Each smart socket (Si) is identified by its unique MAC address (permanent ID) and by a local IP address (temporary ID). The smart socket in this study is designed (for experimental purposes) using Arduino micro-computer device. The smart socket main function is twofold. First it identifies the unit, once the unit is plugged into the socket. An algorithm is designed and hard coded into the Arduino device. The algorithm detects the transient characteristics of the unit, which is used as a unique classifier of the unit [25]. For the experiments conducted in this study, the classifiers were unique for all the devices used in the study. A 98% accuracy was reported in [25] using the Controlled On/Off Loads Library (COOLL) dataset. The SACS system records the transient characteristics classifier for each device and builds a profile for the device. For example, a refrigerator R1 is plugged into the smart socket, the socket measures its transient characteristics, reports it to the SACS, and the SACS determines whether the refrigerator R1 is a new device or a previously recorded device. If the device (R1) is a new one, the SACS records the device with its transient characteristics as a classifier and identifier (IDC). While the device is plugged in, after the initial transient period, the smart socket will report the energy consumption of the device to the SACS, which on its turn maintains energy consumption averages of the device. For practical reasons, it is possible for the classifier of a unit to be identified when the device is used for the first time, using repeated plug and unplug cycles in order to record several variations of the transient characteristics, in a similar manner to fingerprint recording at smart phone devices. The SACS acts as a local server, which records basic information on any device plugged into the system. The information includes IDC, average power consumption, average time while plugged in, priority index, and history of the device usage.

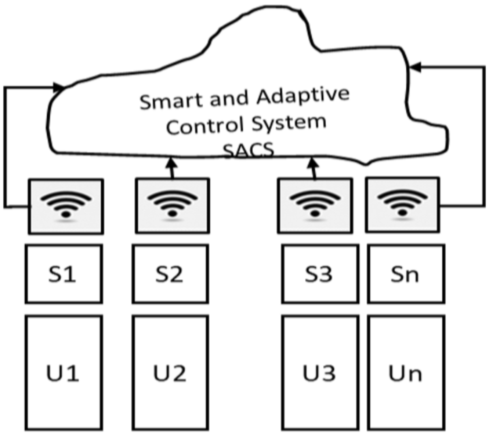

Figure 1: Smart and adaptive control system model

3.1 Algorithm 1: First Come First Served

The SACS uses two variations of the optimization algorithm. Each algorithm can be selected through a configuration file, which can be managed and administered by the household administrator. The algorithms will use the following parameters.

1. Maximum Load Level LMAX. This is a configurable parameter
2. The device identification classifier ID
3. Current load level
4. Device priority parameters PDI
5. The expected time duration of the device TDI
6. The expected energy consumption of the device LDI

Algorithm 1: First Come First Server (FCFS).

```
Step 1: Set The Maximum Load Level LMax
  When a new device (DI) is plugged in
     DO
        {
          Add new device DI
          Detect Device classifier IDCDI
          Get IDC Load (LDI)
         Compute current load:
                Lcurrent = Lcurrent+  LDI
                If Lcurrent ≤  LMax  Accept Device
                 Else Block the device DI
               }
```

Algorithm 1 incrementally adds devices to the current load of the controlled environment. When the load level reaches the maximum configured load level, the system blocks the new device and does not allow it to consume energy. This function is accomplished by the smart socket device, which has the capability of enabling or disabling the electric current flow into the device. The smart socket (SI) acts upon the decision made at the SACS. Algorithm 1 givens preference to devices on a first come first served (FCFS) order. The SACS server can be configured to control the maximum load for a specific time interval, e.g. 30 minutes. This is especially useful in countries such as the USA, where the electric bill contains a significant factor which depends on the maximum load used during a given period of time, e.g. 15 minutes [1, 14].

FCFS algorithm is known for its simplicity, while it guarantees the load level to be within the allowed configured load level. However, the FCFS algorithm suffers from a discriminatory behavior, where devices with lower energy consumption may be disabled and not allowed to join the system, simply because a heavy load consuming device was plugged in earlier. Consider the following examples.

1) *Example 1.* Let the controlled unit (e.g. household) has 5 appliances as shown in Table 1. And the maximum allowed load is 5000 Watt. In this example, 5 devices manage to enter the system, and one with the load (1800) was not allowed because the system had reached maximum allowed capacity. The actual load on the system is 3500, and one device is unable to join. The load utilization is 70%.

Table 1: Example 1 – FCFS

Device Di	Expected Load L_{Di} (W)	Order of Arrival	$L_{current}$ (W)	Status	Device Di
1	2000	1	2000	On	1
2	1000	2	3000	On	2
3	500	3	3500	On	3
4	1800	4	5000	Off	4
5	300	5	5100	On	5

2) *Example 2.* Now assume that the order of arrival changes as shown in Table 2. Note that in this example, three devices are allowed into the system with a total load of 4800 Watts. Load utilization in this example is 96%. As shown in example 2, 2 devices out of 5 will not be able to function until one of the other 3 devices finishes. Obviously algorithm 1 (FCFS) can be credited for its simplicity and ease of implementation. However, the performance and predictability of the system may not be favorable. In a small household unit with relatively low number of devices, the manager can control the behavior of the algorithm in a manner, which allows an optimal scheduling. However, this is not practical for a large establishment, where the number of devices is relatively large.

Table 2: Example 2 - FCFS

Device D_i	Expected Load L_{Di} (W)	Order of Arrival	$L_{Current}$ (W)	Status
1	2000	1	2000	On
2	1000	2	3000	On
4	1800	3	4800	On
5	300	4	5100	off
3	500	5	5600	off

3.2 Algorithm 2: Priority Preemptive (PPA)

This algorithm allows the system to preempt one or more devices in order to accommodate a new device. Of course the device to be preempted must be of the type whose operation can be interrupted such as iron, washing machine, dish washer and the like [9]. Some devices can be considered interruptible given certain conditions. For example, an AC unit may be interrupted if the outside temperature is below 25 ^oC, but is considered uninterruptible when the outside temperature is above 35 ^oC degrees. Life critical devices such as oxygen supplier units are not interruptible at all.

For example, assume that the current load in the system is 9 kW, and the newly plugged in device has a steady state load average of 2 kW and the device has a high priority index. Assume that the maximum allowed load is 10 kW. Evidently, adding the new device causes the load to exceed the maximum configured load. The system knowing that the new device has a high priority, decides to unplug one of the devices with load exceeding 1 kW and with priority index lower than the new one, thus allowing the new device to be added to the system.

Device priority is configured in this study based on several parameters including

1. The average steady state load of the device (LDI). LDI is dynamically adjusted based on the previous uses of the device. For first time use of the device, LDI is set to 0.
2. The expected operation time of the device TDI. TDI is estimated based on previous operation of the device. For first time use of the device, TDI is set to 0.
3. General conditions Index GDI. This index is calculated based on specific external conditions such as current temperature, which is used to define an index priority for AC units, inhabitants of the unit such as children, elderly, people with special needs and other conditions.
4. Initial priority Index (IDI). This is set by the manager.

The priority of a device PDi = f(LDi , TDi , GDi , IDi). PDi is normalized between 0 and 10, where 10 is the highest and 0 is the lowest priority. The calculation of the priority is performed dynamically. Algorithm PPA is shown next.

Algorithm 2: Priority Preemptive Algorithm

```
Step 1: Set The Maximum Load Level LMax
  When a new device (DI) is plugged in
   DO
    {
     Add new device DI
     Detect Device classifier IDCDI
     Find IDC Load (LDI)
     Lcurrent = Lcurrent+  LDi
    If   Lcurrent ≤  LMax  Continue
    Else
      If PDi is higher than PDj
//where PDj is the priority of any plugged in device
  THEN
  Replace PDi with PDj
}
```

Example 3. Assume that a unit system has several devices plugged in with a total load of 4500 Watt and that the maximum allowed load is 5000 Watt. A new device is plugged in with an average estimated load of 1000 Watt. Assume that the priority of the new device is 7.5, and one of the plugged in devices has a priority of 5.5 and load average = 600 Watt. The system will unplug the lower priority device, reduce the current load to 3900 Watt, then the new device with 1000 Watt load demand is allowed to enter the system. The total current load becomes 4900 Watt. The SACS system keeps track of the plugged in devices, their load and priorities.

Note that when a device is unplugged from the system, it remains physically plugged to the smart socket, and the socket will keep trying to rejoin the device, which will succeed whenever a physically plugged device is turned off.

Further optimizations can be applied to Algorithm 2 (Priority Preemptive Algorithm). In this paper, we consider only the Priority Index based algorithm, where the lowest priority device is pre-empted and replaced in case a new device with higher priority needs to be plugged in.

4. Simulation and Results

The system is simulated using a Client Server Architecture. The SACS serves in the system as a server, and each smart socket is modeled as a client.

Two servers are used in this study, one for executing Algorithm 1, and the second one for executing Algorithm 2. Once a smart socket is plugged in, it immediately makes a request to connect to the server, and the server connects the client (representing the smart socket). The server registers the ID of the socket (Its local IP address and Port number). The server maintains the smart socket ID's in its own database.

When a device is plugged into a smart socket, the client representing the socket sends the device data to the server. The data includes the Ampere-Volt (Watt) data. At plug-in time, the client sends the Amp-Volt data at 100 ms intervals. This is necessary for the SACS server to identify the transient characteristics of the device, and identify the plugged in device in case the device had been plugged in before. The SACS server identifies the transient characteristics of the device within a given time interval, sufficient for the device's Amp-Vol data stabilizes near a nominal value. If the device has been used before, the SACS pulls its data from the database and uses the device's previously stored Watt average and use it to decide whether to admit or reject the device based on Algorithm 1 or Algorithm 2. The server keeps a record of the device's average power consumption, and the average plugin time of the device. This information is used in the calculation of the device priority. This data will be used in another study to predict the device health, maintenance requirements, or scrabbling of the device.

The simulation is run for small and large units or households, where a small unit has 20 sockets and a large one has 100 smart sockets, where each socket may be used by several devices over the simulation time.

Figure 2 shows a comparison between FCFS and PPA algorithms for different household sizes (20, 40, 60, and 100 smart sockets per household). Each socket plugs 5 devices over the simulation time. It is shown that the PPA algorithm allows the system to better utilize the load while keeping the load below the maximum configured load. This is due to the fact that PPA attempts to accommodate new devices, even when the maximum load had been reached by replacing one or more of the currently used devices.

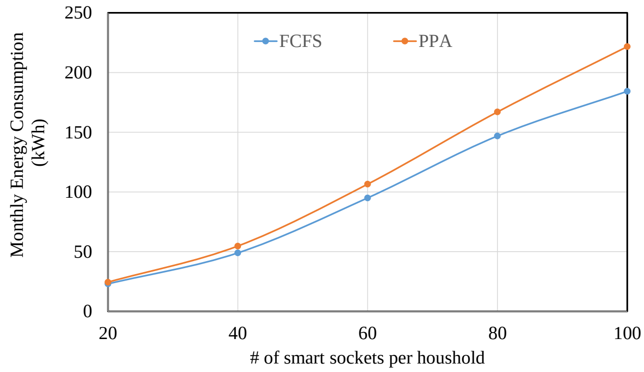

Figure 2: Monthly Energy consumption under FCFS and PPA algorithms with different number of sockets per household whilst keeping the maximum power below 10 kW

Figure 3 compares both algorithms in terms of the number of served devices over the simulation run for different household sizes with the number of sockets per household is 20, 40, 60, 80 and 100 and each socket plugs 5 devices over the simulation duration. It is shown that the PPI algorithm is capable of serving more devices used by the smart sockets for relatively large set of devices in the system. However, for small household units with less than 40 devices the FCFS algorithm has similar performance to the PPI algorithm. Table 3 shows a snapshot of the devices used in the system over a short period of time.

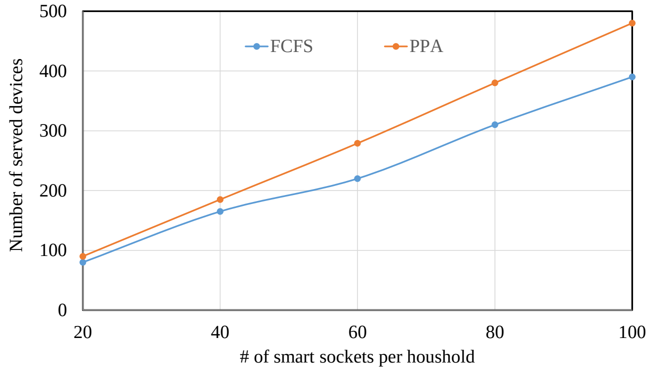

Figure 3: Number of served devices under FCFS and PPA algorithms with different number of sockets per household whilst keeping the maximum power below 10 kW

Table 3: Device usage distribution

Socket ID	Device ID	Time Duration (minutes)	Average Demand (W)
1	1	10	200
1	2	15	700
2	1	60	100
3	1	20	1000
…	…	…	…

Cost Analysis

Here, the cost of electrical bill at a given household is calculated based on energy charge ($/kWh) and peak power charge ($/kVA) [26]. The energy charge is applied to the total volume of consumed energy by the household devices, e.g., 100 kWh. The peak power charge is defined based on both the maximum power drawn during the billing period (e.g., average power each 15 minute period) and the power factor.
In the standard usage of electric power (without any form of control), the bill is heavily impacted by exceeding a given load threshold within a certain interval, usually determined by the power provider company. For example, assume that the total consumption of a given unit is 1000 kWh at $0.1/kWh, the peak power measured at each 15 minute period is 10 kW at $10/kVA, and the power factor is 0.8. Then the electric bill total will be (1000 x 0.1) + (10/0.8 x 10) = 100+125 = $225. Note that the power demand and the power factor contributes significantly to the final bill. In fact the actual bill (to be paid) is more than double the real amount of energy consumed by the customer. The proposed system in this study allows the customer to significantly reduce the bill by controlling the average power demand and the power factor.
Next, we show how the total bill can be reduced by the proposed system. In the above example, the consumer can set the maximum load in a given period of time (e.g., 15 minutes) to 2 kW. The maximum consumption per a billing period of 30 days will be 5760 kWh at a cost of $576. The power demand cost is 2 x 10 = $20 and with power factor at 0.8, the paid power charge becomes 20 x 1.25 = $25 and the total bill is 576+25 = $601. The bill overhead due to online demand is 25/601 = 4% of the total bill cost, which constitutes a significant reduction of the bill.

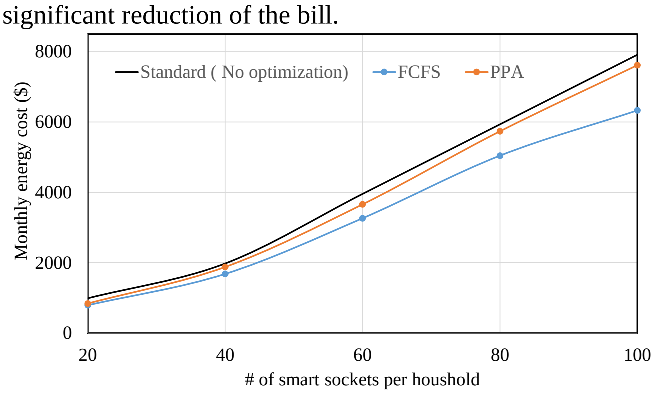

Figure 4: Monthly Energy cost under standard (no-control), FCFS and PPA algorithms with different number of sockets per household

Figure 4 shows the cost comparison using demand management system algorithms FCFS and PPA compared to the standard system with no optimization of the load demand. The major cost charged by electric utility companies is heavily impacted by the real-time power demand by devices of the client, on top of the total consumed energy. Consequently, the reduction of the peak power is the most cost effective means of saving on electricity bills for customers; in the meantime, it enables the network operators to better manage power flows throughout the grid.
In a further research investigation, we will consider the management of power and energy consumption using machine learning algorithms. The actual cost of the power demand control system presented in this study is negligible compared to the saving on power cost.

5. Conclusions

This paper presented a new approach for controlling the power demand by a customer and lowering the power instant supply by the utility company generating the power to meet the customers' demands. The paper presented two algorithms for optimizing average demand per a given period of time.
The first come first serve algorithm (FCFS) is a simple and easy to implement and shows efficiency for small households with less than 40 smart sockets. The priority preemptive algorithm (PPA) is a rather complex algorithm, which provides more control and better utilization to the offered load within a given period of time especially for large household units. Both PPA and FCFS algorithms stream to better optimize the number of served devices and the utilization of

the offered/configured load.
Future work will address different optimization methods, and power factor efficiency optimization.

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