Power Consumption Scheduling for Future Connected Smart Homes Using Bi-Level Cost-Wise Optimization Approach

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Abstract. Future smart-home functionalities enable users to manage their home appliances through a single application by connecting home appliances through an integrated platform and server. In the smart home, a Home Energy Management System (HEMS) is necessary to monitor, control and optimize electrical generation and consumption. On the other hand Demand Response (DR) provides an opportunity for consumers to play a significant role in the operation of the electrical grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives. In this paper we propose an autonomous Demand-Side Management (DSM) model to control the residential load of customers equipped with local power storage facilities as an auxiliary source of energy. In our proposed model the power consumption level of local devices, the amount of power being demanded from both local storage facilities and local utility companies are scheduled using a bi-level quadratic optimization approach of a well-defined convex cost function. Therefore we show that this goal can be fulfilled with a bi-level scheduler unit installed inside the smart meters. In addition our proposed model can also achieve the global optimal performance in terms of energy minimization cost at the Nash equilibrium of a formulated non-cooperative game. We also extend our DSM model to a two tiers cloud computing environment in which both customers and utility companies participate on it.

Keywords: Smart home · Home energy management systems · Demand-side management · Local storage facilities · Bi-level quadratic optimization

1 Introduction

The Smart Grid (SG) is a modernized electrical grid that uses Information and Communications Technology (ICT) to gather information from different parts of power network. This information is used to monitor and control the generation, transmission and

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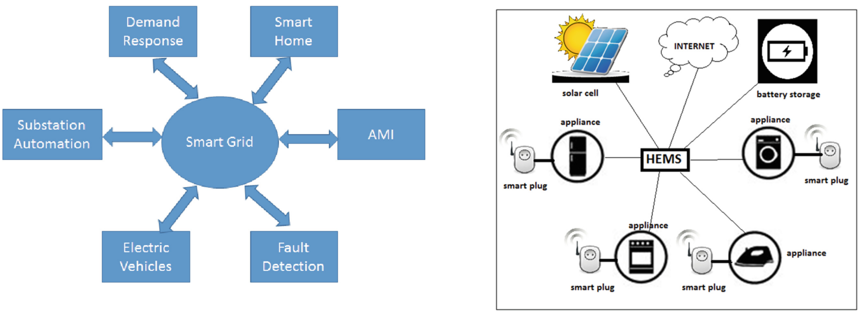
distribution equipment. The SG improves the efficiency, reliability and sustainability of the power grid. It has some unique benefits including: more efficient transmission of electricity, quicker restoration of electricity after power disturbances, reduced operations and management costs for utilities, lower power costs for consumers, reduced peak demand, increased integration of large-scale renewable energy systems, better integration of customer-owner power generation systems and improved security.

A key element of the SG is the availability of a sophisticated Advanced Metering Infrastructure (AMI), capable of real-time communication with the utility company. AMI is an advanced system, incorporating two-way communications to the SG with intelligent applications and communication infrastructure. Using AMI capabilities, it is possible to establish two-way communication between customers and utilities. Smart meters are used to send customer consumption information to the utility and receive control data and price information from the utility. Currently most electricity consumption is in the residential and commercial buildings. Homes and working environments are now isolated, energy-consuming units with poor energy efficiency and sustainability. Based on the Smart Home (SH) concept, these units can be transformed into intelligent networked nodes where a significant part of the energy is locally produced by renewables.

In Fig. 1(a) some applications of smart grid are shown. In Fig. 1(b) an overall view of a smart home is depicted. As shown in this figure, the Home Energy Management System (HEMS) is a proprietary hardware and software system that monitors, controls and optimizes electrical generation and consumption. Smart plug is a WiFi-enabled plug that connects home appliances to the power line and control them remotely.



(a) (b)

Fig. 1. (a) Smart grid applications (b) A smart home

The demand for more electricity has also been growing with the increasing trend in using more electrical devices. It has been changed significantly by the recent advancements in technology and the advent of plug-in hybrid electric vehicles (PHEVs) [1]. Therefore besides allocating more sources of energy to generate electricity, many utility companies try hard to make sure that they can manage the demand for more electricity by the adaptation of well-established demand-side management programs (DSM). These programs will establish practical methods to manage the demand for electricity at the customer side. For this reason, intricate models have been employed which are aimed at reducing consumption or simply shifting it from peak-time hours to non-peak hours during the day. For example in Direct Load Control (DLC) programs, the utility company will manage the customers' consumption level by directly controlling their appliances [2, 3]. However this method ignores the end customers/users' privacy. Therefore a better alternative is the employment of dual or multiple tariffs energy cost systems [4, 5]. In this approach the utility company differentiates between peak-time hours and off-peak hours by applying different consumption costs respectively. Moreover in most of the recent demand-side management programs, the main goal has been on the development of robust models in which the total demand of customers will be reduced at peak-time hours to reduce the cost of power generation [6]. In the next section, some related work in this area is discussed.

2 Related Work

During the past few years, much research has been devoted to DSM programs. Most use optimization techniques and game theory to design an optimized DSM program. There is a rich literature on autonomous demand-side models to manage the demand at the customer side by minimizing the cost of power generation or maximizing the customers' utility [7–9]. However in these models the only entity to generate power is the local utility company. In contrast a recent study has employed a DSM model with multiple utility companies in which customers benefit from maximizing their own utilities by using a Stackelberg game [10].

In [11], a mathematical programming formulation is presented for the fair distribution of cost among smart homes in a micro grid. The authors developed a lexicographic minimax method using a mixed integer linear programming (MILP) approach. The results confirm the performance of the approach in terms of cost savings and fair cost distribution among multiple homes. In [12], a robust approach is developed to tackle the uncertainty of PV power output for load scheduling of smart homes integrated with a household PV system. Simulation results confirm the validity and advantage of the proposed approach. [13] Presents methods for prediction of energy consumption of different appliances in homes. The aim is to predict the next day electricity consumption for some services in homes. The performance of the predictors is studied, and has been shown that the proposed predictor gives better results than other approaches. The authors of [14] present and analyze online and offline scheduling models for the determination of the maximum power consumption in a smart grid environment. Each load model is associated with a proper dynamic pricing process to provide consumers with incentives to contribute to the overall power consumption reduction. The evaluation of the load models through simulation reveals the consistency and the accuracy of the proposed analysis. [15] Deals with the performance analysis of a Global Model Based Anticipative Building Energy Management System (GMBA-BEMS) for managing household energy. The model has been developed in MATLAB/Simulink and evaluated. In [16] an innovative method to manage the appliances on a house during a demand response event has been proposed. A case study with different scenarios has been presented considering a demand response with different durations. Results confirm that the power consumption is reduced. The authors in [17] propose a hierarchical architecture for the utility-customer interaction consisting of sub-components of customer load prediction, renewable generation integration, power-load balancing and Demand Response (DR). A real-time scheduling problem is defined and solved. In [18] a Mixed Integer Linear Programming (MILP) model to schedule the energy consumption within smart homes by coupling environmental and economic sustainability in a multi-objective optimization with ε-constraint method has been developed.

As it can be inferred, in most of the DSM programs, the residential power generation and storage facilities are not considered as active entities in the development of the DSM models. However they can be significantly beneficial in the reduction of residential loads in peak-time hours to help local utility companies to provide more reliable services and reduce costs [19]. Moreover we note that in a recent study, it has been shown that the use of a residential Energy Consumption Scheduler (ECS), a strictly convex cost function and in a non-cooperative distributed game among customers with two-way data and energy communication capabilities, can result in global minimized energy cost at the Nash equilibrium of the formulated game [9]. This approach consider the appliances in two distinct groups of shiftable and non-shiftable devices. The ECS units inside of each smart meter will schedule the consumption level of shiftable devices by minimizing the value of a convex cost function to reduce the demand for electricity during peak-time hours in order to reduce the global cost of power generation.

In this paper we will define an autonomous consumption model that will not only keep the properties of the latter referenced model, but will also consider the local power generation and storage facilities as a substitute source of available power to address the increasing need of customers to consume electricity during the day.

3 System Model

In this section we described out proposed power system model and the properties of the cost function. We will explain how the schedulers minimize the cost of power generation, and introduce our proposed bi-level cost-wise optimization approach.

3.1 Power System

We consider N customers who are connected to each other using smart meters and a two-way data and power communication link. It is also assumed that each smart meter can communicate with the local utility company through the same link. Moreover it is considered that customers can demand for electricity from only one utility company. Each customer is equipped with local power generation and storage facilities which are connected to the smart meters using a separate data and power communication link as shown in Fig. 2.

Throughout the paper, $\boldsymbol{N}$ denotes the set of customers/users that are connected to the grid. For each customer $n \in \boldsymbol{N}$, we also define the vector $\boldsymbol{l_n}$ to denote the total load of each customer at each hour. Therefore the total daily load of each customer can be shown by the vector $\boldsymbol{l_n} = \{\boldsymbol{l_n^1}, \boldsymbol{l_n^2}, \ldots, \boldsymbol{l_n^h}, \ldots, \boldsymbol{l_n^{24}}\}$ where $\boldsymbol{h}$ denotes any hour from the set of hours $\boldsymbol{H} = \{\boldsymbol{1}, \boldsymbol{2}, \ldots, \boldsymbol{24}\}$. Therefore based on the above definition we can calculate the total hourly load of the grid as [9] $\boldsymbol{L_h} = \sum_{n \in N} \boldsymbol{l_n^h}$ and the peak-time hour and the average load level in the local grid will also be calculated as [9] $\boldsymbol{L_{peak}} = \boldsymbol{max}_{h \in H} \boldsymbol{L_h}$ and $\boldsymbol{L_{avg}} = \frac{\boldsymbol{1}}{\boldsymbol{24}} \sum_{h \in H} \boldsymbol{L_h}$, respectively. There is also another important factor in any power system which is called peak-to-average ratio (PAR) that can be also calculated as follows [9]:

$$\boldsymbol{PAR} = \frac{\boldsymbol{L_{peak}}}{\boldsymbol{L_{avg}}} = \frac{\boldsymbol{24\ max_{h \in H} L_h}}{\sum_{h \in H} \boldsymbol{L_h}} \tag{1}$$

Generally lower PAR is preferred due to the impacts of higher PAR values in the increase of global cost of power generation.

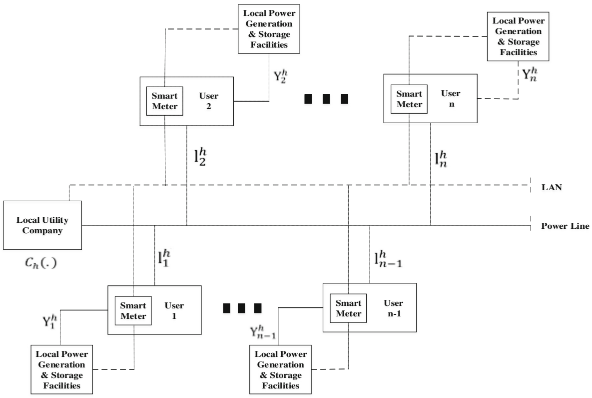


Fig. 2. Block diagram of the proposed system model

3.2 Smart Meter Functionality and Design

As it is shown in Fig. 2, each customer is connected to the grid by the use of a smart meter. We then assume that each smart meter is equipped with two different schedulers, Energy Consumption Scheduler (ECS) and Battery Consumption Scheduler (BCS). The ECS unit is considered to be level one scheduler and is designed to schedule the consumption pattern of shiftable devices to reduce the total load at peak-time hours during the day, as in the referenced model [9]. The BCS unit is also considered to be level two scheduler and is designed to schedule the amount of power being demanded from local storage facilities and the local utility company at the same time.

Smart meters hold a vector $\boldsymbol{X}_{n,a}$ for each appliance to keep track of their consumption pattern during the day. Therefore $\boldsymbol{X}_{n,a} = \left\{ \boldsymbol{X}^{1}_{n,a}, \boldsymbol{X}^{2}_{n,a}, \ldots, \boldsymbol{X}^{h}_{n,a}, \ldots, \boldsymbol{X}^{24}_{n,a} \right\}$ where $n \in \boldsymbol{N}$ is the users' index and $a \in A_n$ indicates any appliances from the set of users' n appliances $A = \{a_1, a_2, \ldots, a_m\}$. Moreover smart meters will also keep track of the amount of power that can be consumed from the local storage facilities by considering a vector $\boldsymbol{Y}_n = \{\boldsymbol{y}^1_n, \boldsymbol{y}^2_n, \ldots, \boldsymbol{y}^h_n, \ldots, \boldsymbol{y}^{24}_n\}$.

Therefore in our proposed model the vector $\boldsymbol{l}_n$ which denotes the hourly consumption level for each user during the day is rewritten as $\boldsymbol{l}_n = \{(\boldsymbol{x}^1_n - \boldsymbol{y}^1_n), (\boldsymbol{x}^2_n - \boldsymbol{y}^2_n), \ldots, (\boldsymbol{x}^h_n - \boldsymbol{y}^h_n), \ldots, (\boldsymbol{x}^{24}_n - \boldsymbol{y}^{24}_n)\}$ where each $\boldsymbol{l}^h_n = (\boldsymbol{x}^h_n - \boldsymbol{y}^h_n)$ denotes the hourly aggregated demand of local appliances $\boldsymbol{x}^h_n$ minus the amount of power that can be consumed from the local storage devices $\boldsymbol{y}^h_n$. Moreover it is important to know that the smart meter will schedule the consumption pattern of each appliance separately using the ECS scheduler and then the hourly aggregated load of the local appliances will be sent to the BCS scheduler for further optimization as shown in Fig. 3. This is done to keep the feasibility of the method to schedule the customers' appliances and to provide all the appliances with the chance of consuming energy from local generation and storage facilities in an optimized manner. Therefore we can calculate the hourly consumption level of local appliances as $\boldsymbol{X}^h_n = \sum_{a \in A_n} \boldsymbol{x}^h_{n,a}$.

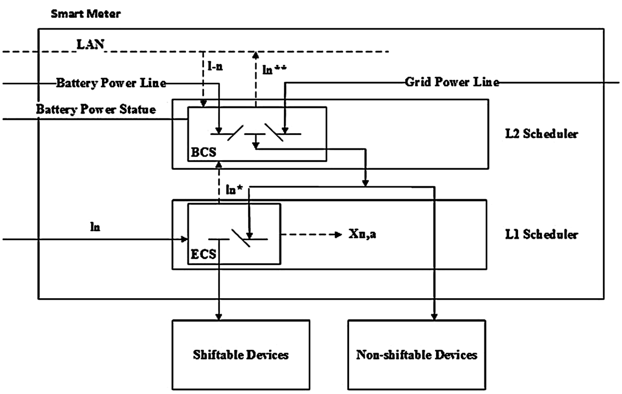


Fig. 3. Block diagram of smart meters showing the ECS and BCS functionalities in our proposed model.

As it is depicted in Fig. 3, the vector $X_{n,a}$ is held in the local memory of ECS unit and is scheduled when an update occurs by user. Then the vector l_n is sent to BCS unit. In BCS unit the vector Y_n is kept in the memory and is used to calculate vector l_n. Moreover the vector Y_n is updated once an optimization is done in BCS units. Therefore the BCS unit schedules the amount of power consumption from local storage facilities to determine the amount of power that should be demanded from both the local utility company and local storage facilities. The hourly demand of electricity from local utility company can be calculated as $\boldsymbol{L}_h = \sum_{n \in N} (\boldsymbol{X}^h_n - \boldsymbol{Y}^h_n)$ where $\boldsymbol{X}^h_n$ is the sum of all the $x_{n,a}^{h}$ for any customer $n \in N$. For the sake of efficiency, it should be mentioned that the BCS units will also keep track of the amount of power being generated each hour by local power generation facilities and the state of the local storage devices in appropriate vectors $\boldsymbol{P_n} = \{\boldsymbol{p_n^1}, \boldsymbol{p_n^2}, \ldots, \boldsymbol{p_n^h}, \ldots, \boldsymbol{p_n^{24}}\}$ and $\boldsymbol{B_n} = \{\boldsymbol{b_n^1}, \boldsymbol{b_n^2}, \ldots, \boldsymbol{b_n^h}, \ldots, \boldsymbol{b_n^{24}}\}$, respectively.

3.3 Energy Cost Function

As it is already mentioned in Sect. 1, we consider a strictly convex cost function as given below [9]:

$$\boldsymbol{C_h(L_h) = a_h(L_h)^2 + b_h(L_h) + c_h} \tag{2}$$

which is used by thermal generators and has two important properties that makes it an interesting candidate to be employed in such models.

Firstly, the quadratic cost function is increasing and secondly the cost function is strictly convex.

However in this model for the sake of simplicity the values for parameters b_h and c_h are considered to be zero. Therefore the cost function is simplified as follows:

$$\boldsymbol{C_h(L_h) = a_h(L_h)^2} \tag{3}$$

Where the only essential parameter to calculate the hourly cost of power generation is the total hourly demand for electricity by each customer. So from expression (3) we have:

$$\boldsymbol{C_h(L_h) = a_h(\sum\nolimits_{n \in N} \sum\nolimits_{a \in A_n} x_{n,a}^{h})^2} \tag{4}$$

Due to the fact that our proposed model is an extension of the referenced model in which the only scheduler is the ECS unit and it can only schedule the consumption level of shiftable devices with no consideration of an available substitute local energy source during the day, we also adopt the same cost function for ECS units, since there is no changes in the function of this unit in our proposed model [9]. For the sake of consistency, we will also adopt the same cost function in BCS unit, however we should investigate the same properties for the proposed cost function when another variable $\boldsymbol{Y_n}$ is added and the result shows that the cost function is also convex when another variable is considered in the model $(\boldsymbol{C_h}\left(\boldsymbol{\theta\widehat{L}_h + (1-\theta)\tilde{L}_h}\right) < \theta \boldsymbol{C_h}\left(\boldsymbol{\widehat{L}_h}) + (\boldsymbol{1-\theta}) \boldsymbol{C_h\tilde{L}_h})$ and will be suitable to be used in our model [20, 21]. We then propose the following cost function to be employed in BCS unit.

$$\begin{aligned} &\boldsymbol{C_h(L_h) = a_h(\sum\nolimits_{n \in N} \binom{h}{n} - \sum\nolimits_{n \in N} (Y_n^h))^2}, \\ &\boldsymbol{C_h(L_h) = a_h(\left(\sum\nolimits_{n \in N} (X_n^h)\right)^2 + \left(\sum\nolimits_{n \in N} (Y_n^h)\right)^2 - 2(\sum\nolimits_{n \in N} (X_n^h) \sum\nolimits_{n \in N} (Y_n^h)))} \end{aligned} \tag{5}$$

As in the referenced model, in our proposed model the price tariffs are also supposed to be adequate enough to differentiate between peak-time hours and the rest of the day. So for the sake of consistency, we also adapt the same values of 0.2 Cents during the morning until 8 am and 0.3 Cents for 8 am to 12 pm. The same negative values are used for the power consumption level from local storage facilities.

3.4 Cost Optimization Problem

Previously it has been shown that the cost function of expression (3) is strictly convex when the only variable for calculating the value of cost function is $\boldsymbol{X_n}$ and is convex when the variables $\boldsymbol{X_n}$ and $\boldsymbol{Y_n}$ are considered to calculate the value of the cost function. Therefore the target cost function (3) can be suitable for use in both ECS and BCS units for the purpose of power generation cost optimization. To do this, we can formulate the cost optimization problem in each scheduler (optimization level) by considering the task that is assigned for each of them. Therefore by considering the task of ECS unit we can formulate the optimization problem which is executed by each ECS unit as below:

$$\boldsymbol{minimize}_{x_n \in X_n, \forall n \in N} \sum\nolimits_{h=1}^{24} C_h \left(\sum\nolimits_{n \in N} \sum\nolimits_{a \in A_n} x_{n,a}^{h} \right) \tag{6}$$

After optimizing $\boldsymbol{X_n}$ by ECS, the BCS unit run the following optimization problem to find the optimized values of $\boldsymbol{Y_n}$:

$$\boldsymbol{minimize}_{y_n \in Y_n, \forall_n \in N} \sum\nolimits_{h=1}^{24} C_h \left(\sum\nolimits_{n \in N} \left(x_n^{*h} - y_n^{h} \right) \right) \tag{7}$$

where X_n^* is the optimized value of X_n which is obtained from expression (6). Each smart meter schedules the consumption level of its local plugged-in appliances at first (level one optimization) and then schedules the amount of available power in the local storage facilities to minimize the daily cost of power consumption (level two optimization). Then each smart meter broadcast the optimized vector $l_n^{**} = \left\{ \left(x_n^{**1} - y_n^{**1} \right), \left(x_n^{**2} - y_n^{**2} \right), \ldots, \left(x_n^{**h} - y_n^{**h} \right), \ldots, \left(x_n^{**24} - y_n^{**24} \right) \right\}$ to other smart meters to inform them of its statue. In this way users play a non-cooperative game with each other to minimize the global cost of power generation in the local grid [9]. Therefore to solve the mentioned problem using the distributed approach, expressions (6) and (7) are rewritten as:

$$\boldsymbol{minimize}_{x_n \in X_n, \forall n \in N} \sum\nolimits_{h=1}^{24} C_h \left(\sum\nolimits_{a \in A_n} x_{n,a}^{h} + \sum\nolimits_{m \in N/\{n\}} l^{**h} \right) \tag{8}$$

$$\boldsymbol{minimize}_{y_n \in Y_n, \forall n \in N} \sum\nolimits_{h=1}^{24} C_h \left(\left(x^{*h} - y_n^{h} \right) \right) + \sum\nolimits_{m \in N/\{n\}} {}_{m}^{**h} \tag{9}$$

4 Simulation Results

In this section, by using computer simulation, we evaluate the performance of our proposed model and compare its performance with the referenced model and the normal consumption pattern in which customers have no participation in any cost reduction program. Therefore in our simulation, we consider 100 customers/users that are signed up to use our cost-wise optimization service. For each user we have considered 10 appliances with shiftable and non shiftable operations. We also consider that each customer is equipped with the average of 10 square meters of photovoltaic cells to generate electricity. Note that the scheduler does not aim to change the amount of daily energy consumption ($\boldsymbol{E}n, a = \sum_{\boldsymbol{h}=1}^{24} \boldsymbol{x}_{\boldsymbol{n},\boldsymbol{a}}^{\boldsymbol{h}}$), but instead to systematically manage and shift it to minimize the energy consumption cost (Fig. 4). We also defined soft but adequate constraints for the optimization vectors $x_{n,a}^h$ and Y_n^h in each level as mentioned before.

In addition, in an interesting result, we note that by scheduling the amount of power consumption from local storage devices in BCS units, the fluctuations in the amount of hourly demands for electricity will be answered by local storage facilities rather than the local utility company that will lead to a more smoothened power demand from the local grid as shown in Fig. 5.

It also has to be mentioned that as it is expected, the value of PAR is decreased in both referenced and proposed models in comparison to the normal model in which customers have no participation in any consumption scheduling program. Results confirm that the value of PAR for normal, referenced and proposed models are 1.98, 1.27 and 1.4, respectively. As it can be inferred, the cause of increment in the value of PAR in the proposed model in compare to the referenced model is the higher rate of reduction for average value of total demand in the grid than the reduction rate of the maximum value of that after the level two optimization. This would be the result of power consumption from local storage facilities.

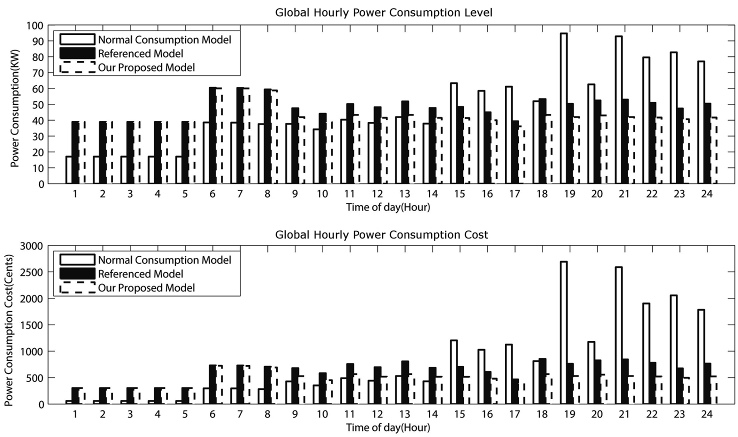


Fig. 4. The total hourly power consumption level (top) and consumption cost (down) in the grid, a comparison between normal, referenced and proposed models.

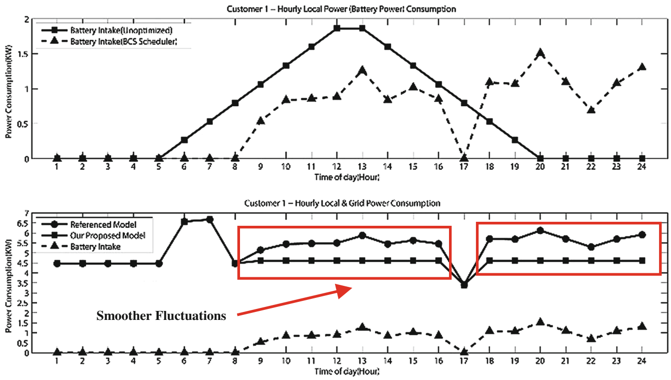


Fig. 5. Hourly comparison of consumption level from local storage facilities (top) and comparison of hourly consumption level of referenced and proposed model (down)

5 Extension to Cloud Computing Environments

The advent of AMI has increased the level of data collection dramatically. There are different sources of “Big Data” in utilities which use smart grid applications in their networks. Some of these sources are: smart meters, grid equipment, off-grid data sets, home devices and substation sensors. To cover the processing and storage requirements of new smart grid applications, cloud computing is a good solution. Recently cloud computing has received attention for smart grid applications [22–24]. Most smart grid applications need reliable and efficient communications system. This can be met by utilizing the cloud computing model. As investigated in [24], cloud computing brings some opportunities for smart grid applications. Flexible resources and services shared in network, parallel processing and omnipresent access are some features of cloud computing that are desirable for smart grid applications.

Using the processing and storage capabilities of the cloud computing, it is possible to solve expression (6) and (7) centrally. We believe the reference model [9] has the following major problems: (1) We should classify all customers in some clusters with N users and provide communication protocol for all of them. (2) We need sophisticated HEMS or smart meter to run the optimized problems. This has more cost for the users. (3) The security is a major problem. If a hacker access the smart meter, he/she can change all users’ consumption and scheduling information, and broadcast wrong information for the other users in the cluster. So the user privacy still remains a main challenge. By developing the Internet of Thing (IoT) technology, it is possible to connect each customer appliance to the cloud and control and schedule it centrally. As shown in Fig. 6 the proposed demand side management program can be implemented in a two tier cloud computing environment such as SAVI network [25]. The local edge cloud is responsible to store the load consumption information of customers. The DSM program is run at local edge cloud to optimize power consumption of local customers and minimize the customer’s cost. At the core cloud all information from edge cloud are collected. Using this information it is possible to predict the total demand load in the network. Based on the total load and the amount of generated power, the utility company determines the new price. The new price is forwarded to the edge cloud which the DSM program is running. The DSM program compute the new scheduling pattern and send it to the smart meter or HEMS to be applied to the home appliances. Using a web based portal, any customer can login to the system and gets information about the current consumption and cost. It is also possible to remotely control some devices in the home. Using social media networking, all customers can share their usage information and compare their power consumption and costs together.

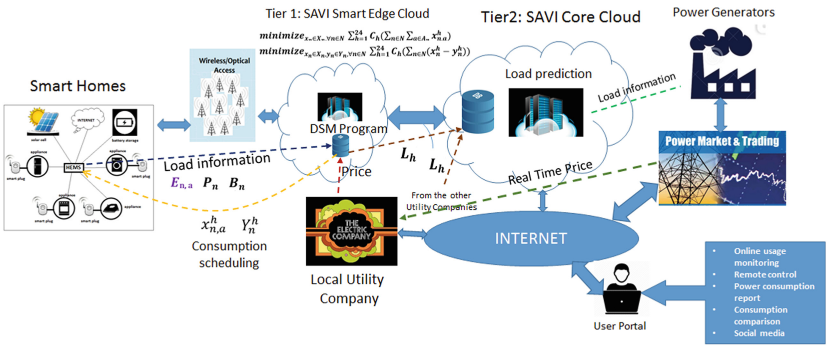


Fig. 6. Extension of the proposed model in SAVI cloud

6 Conclusion and Future Works

In this paper we proposed an autonomous model to schedule the consumption level of customers who are equipped with local power generation and storage facilities in a way that the global optimal performance in terms of energy minimization cost can be achieved. The proposed model has been designed to schedule both the consumption level of local appliances and the amount of power consumption level from local storage devices simultaneously by the use of a bi-level optimization approach. Moreover by the consideration of soft but adequate constraints on the optimization vectors the stimulation results indicate that the proposed model can reduce the cost of power generation in the local grid to a more interesting level in compare to the normal and referenced consumption model which led us toward a more reliable grid as an important energy infrastructure in future smart cities. We believe using cloud computing benefits, it would be possible to design and implement an optimized demand side management program that both customers and utility companies participate on it.

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