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Load Scheduling with Maximum Demand and Time of Use pricing for Microgrids

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Load Scheduling with Maximum Demand and Time of Use pricing for Microgrids

A Dissertation submitted in partial fulfillment of the requiremnts for the degree of

Doctor of Philosophy at Virginia Commonwealth University

By

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To My Mother:Zainab Yousif
&
To my Uncle: Ya'agoob Yousif

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Abstract

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Several demand side management (DSM) techniques and algorithms have been used in the literature. These algorithms show that by adopting DSM and Time-of-Use (TOU) price tariffs; electricity cost significantly decreases, and optimal load scheduling is achieved. However, the purpose of the DSM is to not only lower the electricity cost, but also to avoid the peak load even if the electricity prices low. To address this concern, this dissertation starts with a brief literature review on the existing DSM algorithms and schemes. These algorithms can be suitable for Direct Load Control (DLC) schemes, Demand Response (DR), and load scheduling strategies.

Secondly, the dissertations compares two of DSM algorithms to show the performance based on cost minimization, voltage fluctuation, and system power loss [see in Chapter 5]. The results show the importance of balance between objectives such as electricity cost minimization, peak load occurrence, and voltage fluctuation evolution while simultaneously optimizing the cost.

The second optimization algorithm has potential to provide more value to the customer in reducing the cost. This is done by evaluating the voltage of the entire system and subsequently avoiding the use the appliances at high peak load during the time when the electricity price period is high. In other words, a good DSM algorithm should have the objective to minimize the electricity cost for the customer and maximize the customer convenience to handle large number of appliances of several types.

The objective of the first part of the dissertation is to set up an optimization model for the offline household demand side management. The goal is to reschedule the energy consumption, taking into account the day-ahead dynamic electricity price [13] and the real production of the photovoltaic system.

The proposed optimization-based model aims to reduce the total electricity bill but ensuring a comfortable user experience at home. This model can effectively minimize the energy consumption cost for day-ahead time horizon according to the forecasted electricity price.

Compared to other related work in the literature, this work has following key contributions: 1) the proposed DSM model incorporates economic benefits of local solar PV generation along with negative impacts on voltage fluctuations and deviation in the distribution network. It should be noted here that most reference works ignore voltage problem in the presence of photovoltaic system. 2) The first part proposes a practical model for demand side management with a flexible penalty approach to account for the inconvenience caused by deviation from customer desired schedule. In other words, customer inconveniences caused by DSM schedule will be translated into additional compensation cost in the optimization objective function which is calculated based on some customized rate and intends to effectively discourage or reduce unnecessary load shifting or changes.

In the second part of the dissertation, an optimization model for a multiple residential households and two size of commercial loads small and large with a rooftop PV installation was implemented. This algorithm can take into consideration the evolution of the system performance in terms of operation parameter such as voltage fluctuation, power loss of the entire system, and the PV utilization efficiency while optimizing the electricity cost. In addition the proposed algorithm can handle large number of controllable appliances in two types of loads residential and commercial taking into consideration the fact that certain appliances may have higher priority over other appliances so that these appliances may be shifted to the suitable time. In the simulation process the algorithm classifies the commercial appliances into three categories: high, med and low. The appliances in each category subjected to different penalty prices according to the importance of the appliance.

The key technical contributions of the third part made in this thesis can be summarized as follows: (1) An optimal load scheduling approach exploited to appropriately manage the operations of appliances and allocate the domestic appliances to the time slots with low costs in accordance to the day ahead price information provided by Virginia power company; (2) based on the Clonal Selection Algorithm (CSA), an optimization method is designed and implemented to achieve the optimal schedule that can help consumer to minimize the daily energy cost; (3) study the advantage of using small isolated power system of PV profile to be connected to the household to study the contribution of this source on the energy cost, this study deals with power scheduling in PV using the clonal selection algorithm (CSA) to obtain the least cost of electricity.

CHAPTER 1

1.1 Introduction

Considering the pressure on global natural energy resources, the new power grids aim to enable the customers to play a virtual role as an active participant instead of passive consumption points. With this in mind, and based on the real-time electricity prices, the smart end-users can reduce their consumption cost by scheduling their pattern of electricity usage. Indeed, active end-users can receive relevant technical data from the load service entities and plan the operation of all appliances with the predefined aim under typical constraints such as costumer preferences and load service restrictions [1]. With this motivation, several approaches are recently suggested for the optimal in-home power consumption.

Demand Side Management (DSM) techniques are used and implemented to schedule loads at the consumer level to save energy, reduce cost, and help grid operation; however, it is impractical to request a consumer, who is neither an economist nor an experienced grid operator, to create an optimal schedule from the many possibilities [2]. Therefore, implementation of load scheduling methods helps consumers to maintain low energy cost. Demand side management also plays a significant role in the electricity market [3] [4]. DSM generally refers to actions taken by the consumer to change the electricity demand in response to variations in the electricity prices over time [5].

1.2 Overall Objective

The objective of this work is to set up an optimization model for the offline household demand side management. The goal is to reschedule the energy consumption, taking into account the day-ahead dynamic electricity price [13] and the real production of the photovoltaic system. The proposed optimization-based model aims to reduce the total electricity bill but still ensure a comfortable user experience at home. This model can effectively minimize the energy consumption cost for day- ahead time horizon according to the forecasted electricity price. As such, our work is focused on two distinct applications: 1) proposed household DSM model is aimed to minimize the electricity cost by scheduling the on/off status of domestic appliances over the operational periods, considering the dynamic electricity prices, locally available PV generation, and the penalty prices of appliance operation time-shifting which are included in order to manage the customer inconvenience caused by the proposed DSM program , and 2) extends the single household case to that of multiple households and commercial load. Using the developed simulation model we evaluate the performance of decentralized DSM and study their impact on the distribution network operation and renewable integration, in terms of utilization efficiency of rooftop PV generation, voltage fluctuation and real power loss.

For the first application proposes a DSM model incorporating economic benefits of local solar PV generation along with negative impacts on voltage fluctuations and deviation in the distribution network. It should be noted here that most reference works ignore the voltage problem in the presence of photovoltaic system. Also, this model proposed a practical model for demand side management with a flexible penalty approach to account for the inconvenience caused by deviation from the customers desired schedule. In other words, customer inconveniences caused by a DSM schedule will be translated into additional compensation cost in the optimization objective function which is calculated based on some customized rate and intends to effectively discourage or reduce unnecessary load shifting or changes.

For the second application, we proposed a framework to study both commercial and residential decentralized demand side management together in a radial distributed network. Each smart building makes individual appliance scheduling to optimize the electric energy cost according to the day-ahead forecast of electricity prices and its willingness for convenience sacrifice.

For practical modeling of DSM for different load types, a compound penalty price is considered to account for appliances importance and customer willingness for DSM participation.

Using the developed simulation model we examine the performance of decentralized DSM by comparing its impact on the distribution network operation and renewable integration, in terms of utilization efficiency of rooftop PV generation, voltage fluctuation and real power loss. It is found that in a distribution network which includes both residential and commercial loads, residential DSM has better performance in sense of electricity cost saving, energy loss reduction and voltage fluctuation.

Demand Side Management (DSM) strategies are often associated with the objectives of smoothing the load curve and reducing peak load. Although, the future of demand side management is technically dependent on remote and automatic control of residential loads, the end-users play a significant role by shifting the use of appliances to the off-peak hours when they are exposed to day-ahead market price. This work proposes an optimum solution to the problem of scheduling of household demand side management in the presence of PV generation under a set of technical constraints such as dynamic electricity pricing and voltage deviation.

The proposed solution is implemented based on the Clonal Selection Algorithm (CSA). This solution is evaluated through a set of scenarios and simulation results show that the proposed approach results in the reduction of electricity bills and the import of energy from the grid. Simulation was carried out assuming three types of appliances: base line load, uninterruptible and interruptible appliances using the Clonal Selection Classification Algorithm (CSCA), an artificial immune system technique that inspired by the functioning of the clonal selection theory. This proposal also studies power scheduling in a PV base renewable system using CSA, to obtain the least cost of electricity. It encourages people to make use of possible wind and solar potential from the environment aspect.

1.3 Background Information

In recent years, the electricity networks have started to change, with a wide range of distributed energy suppliers from wind turbine to photovoltaic systems. Along with distribution networks, modern communication infrastructures have also begun to be installed, in order to support and improve the reliability and efficiency of the power networks [1]. In this new electricity network, a large number of data sets are available for residential consumers to improve the energy consumption policies, by means of changing their habits in using household appliances [2], [3]. In order to evaluate the effectiveness of an energy management system, electricity demand needs to be analyzed in a high-resolution fashion [3]. This is required in order to identify which type of electricity activities can be modified without any weighty impact on the consumers lifestyle and freedom [4]-[5]. During the last decade, various models have been proposed to define household demand side management strategies for improving the performance of the distribution networks.

But the focuses and contributions of the models tends to be different. Reference

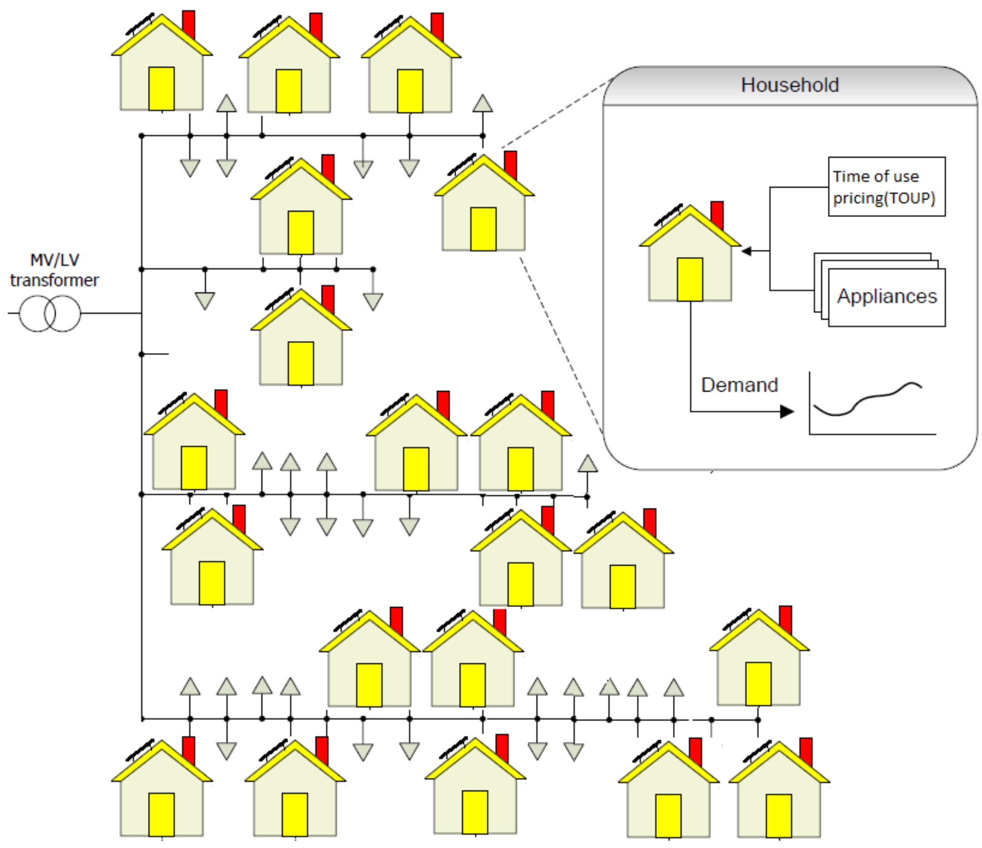

Fig. 1. Overview of electricity Distribution network

[6], proposed a model that based on devices future usage, the consumer is able to optimally schedule home appliances activities for the next day and with the goal of minimizing the electricity bill. In [7]-[8], real-time monitoring system is presented as an effective way to improve the efficiency of different control methods in the energy management system. This model provides a great potential to control the activities of appliances especially the indoor temperature control devices. In reference [9]; the design of a genetic algorithm based control method is presented in order to reduce the electricity bill but still consider user freedom at home. According to the results presented in [9], this method can reduce the total electricity cost considering the real-time monitoring system and the electricity price. In reference [10], the authors propose an approach to model consumer demand at the appliance level.

Regarding the impact of renewable energy resources, many research works have been carried out in the literature. A high penetration of distributed generation can lead to problems in low voltage distribution networks. In [11], the authors proposed an active DSM model to address issues of integration of renewable energy resources in distribution networks, this dissertation considered uncertainties in load and power and proposed multi MGs power dispatch at smart distribution grids. Reference [12] provided a mathematical definition for electricity generation optimization in a typical residential load with different energy systems combined heat and a battery system. Demand side management (DSM) aims to efficiently manage electrical power consumption by engaging energy customers, through offering incentives and price-based signals to alter their consumption patterns or directly controlling their loads [14]. DSM has attracted significant attention among the DSM research.

References [15] and [16] proposed algorithms to schedule the residential loads and minimize the electricity cost. Authors in [17] proposed a scheduling approach of operation and energy consumption of various electrical appliances in a grid connected smart home system. Reference [18] developed a multi-household simulation framework to study the decentralized DSM in a residential distribution network. In [19], a coordinated algorithm is proposed to minimize the users payments. The proposed algorithm controls both the household load and distributed energy resources (DERs) (e.g., PV units).

In reference [20], demand side management strategy is proposed for smart grid for three different areas: residential, commercial, and industrial. This strategy is based on load shifting technique for future smart grid. A new optimization technique with a simple linear programming algorithm was used to minimize the energy cost based on real-time demand response and renewable energy resource [21]. Reference [22] provides a home energy management approach based on the neural network analysis with respect to PV and energy storage system.

The major goal of DSM in References [1]-[6] is to efficiently manage the loads is such a way that will eventually improve the efficiency of the grid, reduce costly generation, decrease excessive load pressure, increase power system stability and sustainability by maximizing system capacity without changing whole physical infrastructure of the power system. For instance, when researchers in [1] and [2] focused on the household DSM, they mainly neglected PV utilization efficiency, maximum demand limit, and the customers welfare. While load scheduling schemes for scheduling residential loads consumption proposed in [3]-[5]. Ref. [4], a combination of DSM and TOU tariffs, significantly decreases the cost of energy with a high utilization of PV generation power using a heuristicbase load scheduling scheme is proposed in [3], these references preset a demand side management strategy based on load shifting technique in three service areas; residential commercial and industrial.

In some references authors take into the regard the priority of the operation time for each appliance by proposed time delay function to minimize the customer discomfort. In this work the price rate signal used in the residential load different from the price rate used in the commercial load. Ref [5] proposed a multi sage optimization for a typical home energy with assuming a rooftop solar PV; the first thing to mention in this paper is that the proposed algorithm assumed that the surplus power will injected to the grid with a reward, the second thing is that the case study of this paper considered the appliances preference and no penalty was assumed for the shifted appliances. In [6], a residential load scheduling approach proposed to manage the operation time and to achieve optimal daily usage of DGs that locally available, a genetic algorithm is designed and implemented and two levels of optimization based on the DG based scheduling and RTP-based scheduling, while in our work the objective function minimize the cost by finding optimal load schedule and make the best use of PV generation power. Our objective function we include penalty cost and power loss.

DSM can also be performed by using Direct Load Control (DLC). References [7]-[15] illustrate that DSM can be performed by using DLC, utility manage the customer consumption using this method, and customers appliance can be controlled by information technology (IT). Different types of algorithm are used for DLC, the authors propose an optimization algorithm that can apply with either on or of time to manage and control the load in residential and industrial. Also, its found that DCL can also be used to reduce the peak load for the large scale residential demand response implantation. Different optimization techniques based on dynamic programming are used to achieve the optimal DLC strategy. For example, a Genetic algorithm is used to optimize the scheduling of direct load control (DCL) strategies, and integer linear programming .Its mentioning that in some DLC optimization algorithm used only for certain appliances in a household, for example refrigerator, or air conditioning . However in our work the algorithm implemented used was developed to cover a variety of appliances in different types of loads such as commercial loads and residential.

In references [16]-[24], Demand Response (DR) where users are motived to be an active participant to manage their loads by reducing their consumption at peak load hours can be the alternative of the DLC. In this regard, the most common DR includes critical-peak pricing (CPP), time-of-use pricing (TOUP), and real-time pricing (RTP). For example, in RTP tariffs, the price of electricity changes at different hours of the day, while the in TOUP electricity prices are previously determined and the consumer shifts the operation time of the load accordingly. In real time pricing the problem is that it is difficult and confusing for the consumer to respond to the variation in the price every hour also peak load may occurs in the low-price time period. The peak load may cause instability in the system; therefore, it would be important to deploy TOUP price with max demand limit as block rates. In fact, this what we include in our research project while we apply the optimization scheduling technique.

Several methods and studies have been implemented over the past two decades in order to minimize the electricity cost-based day-ahead price. In these references DLC algorithm using linear programming was developed, the results show that the electricity cost charged to the customers reduced after participating in DCL program. Its worth mentioning that smart pricing adopted to achieve lower electricity cost, propose power scheduling for demand response in smart grid system, results show that the proposed scheme leads to reduce the peak demand.

References [21]-[24] proposed direct load control based on a linear program algorithm to manage large number of customers with controlling appliances in order to achieve maximum load reduction. These linear program models were developed in the references to optimize system peak period load reduction in commercial and residential loads. Also, the authors adopted some heuristic based evolutionary algorithm (EA), these algorithms were also used for energy management applied for load scheduling for DCL based on load shifting, and this algorithm easily adapts heuristic in the problem. In our proposal Colonial Selection Algorithm (CSA) method is based on the biological immune system and the natural defense mechanism of human body. In CSA the limitation is that the quality of the results depends highly on the initial population and the probabilities of the mutation. The population size in our work makes the algorithm converge towards high quality solutions within a few generations, also its easy to implement and fast convergence.

The main difference between CSA and PSO is that PSO doesnt have genetic operators with such mutation, but both CSA and PSO shares one aspect thats is they have memory which means they save the last iterations and updates during the optimization process. According to literature in these references, PSO is similar to the genetic algorithm GA as they both have population-based search, in PSO the memory is important to the algorithm.

In references [25]-[28] to the problem of scheduling of household demand side management in the presence of PV generation took more attention. For instance, in [25] optimal scheduling and controlling approach which performs the scheduling of household appliances and management of local energy resources has been studied. A high penetration of distributed generation can lead to problems in low voltage distribution networks, for this there exists a good review of the literature in these references mainly focused on PV penetration limit due to voltage violation in the low-level networks. Some of the proposed techniques are based on real-time demand response and renewable energy. The proposed techniques do not consider the importance of balance between the objectives, such as energy cost minimization, peak load minimization and user evaluation of voltage fluctuation, also the voltage monitoring part was absence from the constraints, and beside the voltage limitation has to be taken into account. In another word, a good DSM algorithm should have an objective that should cover the minimizing the electricity cost and maximizing the consumer convenient and handle a large number of appliances of several types.

References [29]-[38] focused on load scheduling methods based on a day-a head optimization process to reduce the users electricity bill by producing or storing energy to lessen their energy purchased from the grid. Load management technique for the air conditioner enable a consumer with small air conditioner appliances to participate in various load management programs such that they can be motivated by incentives from the utilities to lower their monthly electricity bills. The work in [36] smart load management is developed for coordinate the scheduling electric vehicles, considering the grid performance such as voltage limit and the total system power loss. In [37] and [38] distribution charging problem in electric vehicle propose, the authors proposed model aims to find the optimal starting time for charging the battery to minimize the cost delivered by the transformer.

The DSM techniques used in [39]-[42] reduce the peak load of the grid proposed, the idea in this technique that the load demand provides from the user side using the smart power system and the energy provider update the energy price accordingly. The outcomes these references illustrate that the daily power consumption pattern can be smoother and more controlled through different DSM schemes. For example, the Demand response scheduling under load uncertainty based on real-time pricing in a residential grid presented in [40, 41, and 42]; in these references, the authors used game theory to obtain the optimal load consumption pattern based on provided price, and the authors model the interaction between the energy provider and the consumer using game theory.

In [43-49] researches covered optimization of the performance of the micro grid to make the best use of the renewable generation resource and to reduce the dependency on grid energy provider. For example, in [43] and [45] propose energy management system models including PV generators with storage units. While in [44] the author introduces a residential PV generation energy storage system that considers the pattern of daily operation load of the homeowner. The benefit of a storage system in local residential PV installation is presented in [46] and [47], where the authors study the impact of PV on the quality of the low voltage network.

In addition, works [48] [51] proposed scheduling schemes in smart grid environment, in order to improve the quality of the power grid and to enable the consumer to reshape his production and consumption pattern. Moreover, these references are optimal residential load scheduling models using mixed integer linear programming. The proposed model also presents the integration of the renewable generation with a battery storage system. The model aims to help the consumer reschedule the appliances to get optimal benefit and to minimize the electricity bill. The author in [50] proposed an optimal scheduling technique for residential appliances in smart home with local PV generation; Results indicate that the proposed strategy has the capability of maximizing the savings in electricity cost. The work in [51] studies scheduling of different types of appliances by adopting dynamic programming-based game theoretic approach. Its assumed that the consumers with extra power generation can sell with specified price so that they can reach the maximum revenue and reduce their electricity bill.

1.4 Limitations of the Current Micro grid Literature. Contribution

Based on the conducted literature review, we can see current related work.

1. The DSM programs that have been used (e.g. [33], [34], [41]), proposed an efficient energy management system to schedule the electricity use of appliances to achieve the maximal benefits for customers considering all three types of appli-

ances; base, interruptible, and curtailable appliances. The proposed algorithms do not consider the importance of balance between the objectives energy cost minimization, and peak load minimization. While in this work, a DSM model is proposed and mathematical models for the grid, and renewable energy resource represented by rooftop PV generation are presented as well as for different type of electrical appliances in different types of loads commercial and residential. This model can effectively minimize the energy consumption cost for day-ahead time. consumption cost for day-ahead time.

2. The DSM techniques and algorithms used in [12], [14], and [27]. propose a consumption scheduling mechanism for home area load management in smart grid using integer linear programming (ILP) technique Most of them are system specific [12], [13], [10], and some of which are not applicable to practical systems that have a wide variety of independent appliances. Moreover, the techniques were developed in [10], [19] using a linear program. These algorithms and techniques cannot handle a large number of controllable devices from several types of loads which have several consumption patterns.

3. The (time of-use price) TOUP methods proposed in [38], [40] and [46] applied to achieve low electricity cost. However, the purpose of the demand side management is not only to achieve optimal electricity cost but also to prevent higher power demand peaks even if the electricity price is low. From this point of view, TOUP applied in these references still has one defect which would be that it causes the demand to be shifted to hours with low electricity price, and that would lead to a higher peak electricity demand and peak-to-average ratio during the low-price time. Therefore, a combination of time of use price with a fixed threshold which represent max demand is necessary.

4. Most of DLC optimization algorithms are used for certain appliances in a household, for example refrigerator and air conditioning [34] - [37] which are categorized as residential load. However, in this work, the algorithm implemented used was developed and expanded to cover a variety of appliances in different types of loads such commercial load and residential household although they have different characteristics in terms of load profile, electricity price, appliances, and their customer willingness for DSM participation.

5. Ref. [17], appropriate TOUP profiles were used for both residential and commercial loads. In fact, the profiles were different for each load [49]. This algorithm takes into the regard the voltage fluctuation evaluation and the power loss of the entire system while optimizing the electricity cost. The goal is to reschedule the energy consumption, considering the day-ahead dynamic electricity price and the real production of the photovoltaic system.

6. According to [24] PSO the limitation is that the quality of the results depends highly on the initial population and the probabilities of the mutation. The population size in my work makes the algorithm converge towards high quality solutions within a few generations, also its easy to implement and has a fast convergence. The main difference between CSA and PSO is that PSO doesnt have genetic operators with such mutations, but both CSA and PSO shares one aspect in that they have memory which means they save the last iterations and updates during the optimization process. The PSO is similar to the genetic algorithm GA as they are both population-based search, in PSO the memory is important to the algorithm.

The proposed approach may be used in demand side management systems to help household owners to automatically create optimal load operation schedules based on comfort settings of choice and in the presence of dynamic electricity pricing and PV system or can be manually controlled or programmed using a set . In appendix B a table of existing models for DSM used for energy management some of these references discussed results applicable for program managers who are considering Home Energy Management System (HEMS) programs , HEMS can be broadly defined as a system that enable households to manage their energy consumption (including hardware and software linked via a network)[76]. According to Ref. [77] HEMS Can be in different forms.

Summary

This part of the dissertation gives a brief survey of DSM techniques and algorithms. The DSM programs that have been used in some references proposed an efficient energy management system to schedule the electricity use of appliances to achieve maximum benefits for customers considering all three types of appliances; base, interruptible, and curtailable appliances.

According to the conducting survey :

1. **Monitoring the system operational condition while minimizing the energy cost.**

   The proposed algorithms do not consider the importance of balance between the objectives, while the main advantages of our proposed algorithm is the ability to monitor the voltage fluctuation and power loss of the entire system while optimizing the electricity cost and avoiding the peak load occurrence.

2. **The proposed algorithm can handle large number of controllable appliances.**

The proposed DSM model is proposed and mathematical models for the grid, renewable energy resource represented by rooftop PV generation are presented as well as for different type of electrical appliances in different types of loads commercial and residential. This model can effectively minimize the energy consumption cost for day-ahead time.

3. **Modeled the customer inconveniences caused by DSM schedule.**

   The customer inconveniences caused by DSM schedule will be translated into additional compensation cost in the optimization objective function.

4. **The Operation time of the appliances.**

   The proposed algorithm also take into consideration the fact that certain appliances may have higher priority over other appliances so that these appliances have to operate in their specified time; hence these type of appliances have less DSM participation.

1.5 Demand Side Management Techniques:

Six main methods are included in DSM techniques to alter the load profile curve. These are: 1) peak clipping 2) valley filling 3) load shifting 4) strategic conservation 5) strategic load growth and 6) flexible load shape. In Fig. 2 these six DSM strategies are illustrated [3], [52]. Cutting off the peak which is higher a certain load range is called peak clipping. In case of peak clipping, load is directly controlled to reduce the stress of demand during peak period, but consumers comfort will be effected accordingly.

Valley filling means rise the loads in the off-peak period by using the storing energy in batteries or charging electric vehicles [53]. Load shifting technique aims to shift some of the load during the on-peak loads to off-peak periods, thus lessen the

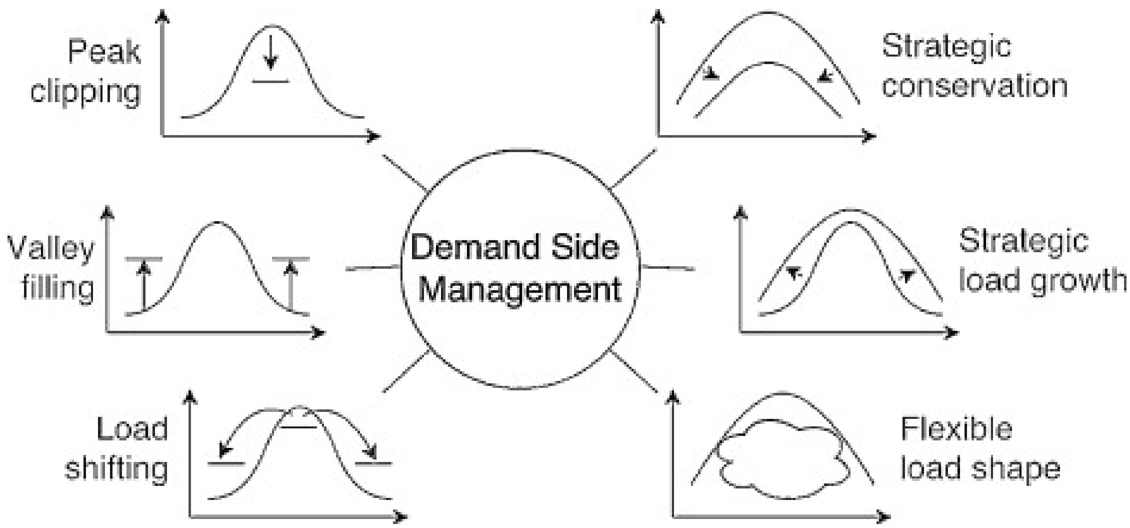

Fig. 2. Basic load shape techniques [17]

high-power demand during peak load time. Load shifting technique is widely applied as the most efficient load management in the distribution networks. At consumer sites by directly apply demand reduction technique, strategic conservation aims to achieve the optimal load consumption profile. In case of large demand, regular response is optimized by strategic load growth. The reliability of a smart grid is prominently dependent on the Flexible load shape. Utilities stimulate the consumers through various incentives to be willingly participate in the load control scheme during critical load periods. [19]. Different DSM techniques are applicable in different cases taking into the regard the concept of applying optimizing algorithm.

The proposed approach may be used in demand side management systems to help household owners to automatically create optimal load operation schedules based on comfort settings of choice and in the presence of dynamic electricity pricing and PV system or can be manually controlled or programmed using a set . In appendix B a table of existing models for DSM used for energy management some of these references discussed results applicable for program managers who are considering Home Energy Management System (HEMS) programs , HEMS can be broadly defined as a system that enable households to manage their energy consumption (including hardware and software linked via a network)[77]. According to Ref. [78] HEMS Can be in different forms:

1.6 Demand Side Management in smart grid:

In the power network system, the advance technologies enabled two way of communication involving advance sensors, intelligent control, self-maintain grid, control strategies and measuring capability for the growing of the widespread monitoring, security of delivering and reliability of the power network, which these days can be termed as Smart Grid [1]. Smart Grids major challenge is the ability of connecting the utilities and the customers with the help of bidirectional connection to ensure efficient demand side management.

The main purpose of DSM is to efficiently reshape the loads is such a way that will eventually improve the efficiency of the grid, decrease the cost of the generated power, reduce the excessive load peak, and increase the network stability and reliability by maximizing power system capacity without adding more generation unites. [53]. Existing grids transformation into smart grid will open a pristine future of demand side management. From renewable energy resources, a major portion of generated electricity is expected to be utilize in a smart grid, although they are discontinuous resources, so the uncertainty is a challenge for the grid. Load control techniques became important for such scenario. Moreover, DSM system should be capable of dealing with the grid communication infrastructure between manageable loads and central controller [5], [6].

The range of various stander of optimal load consumption can be very broad.

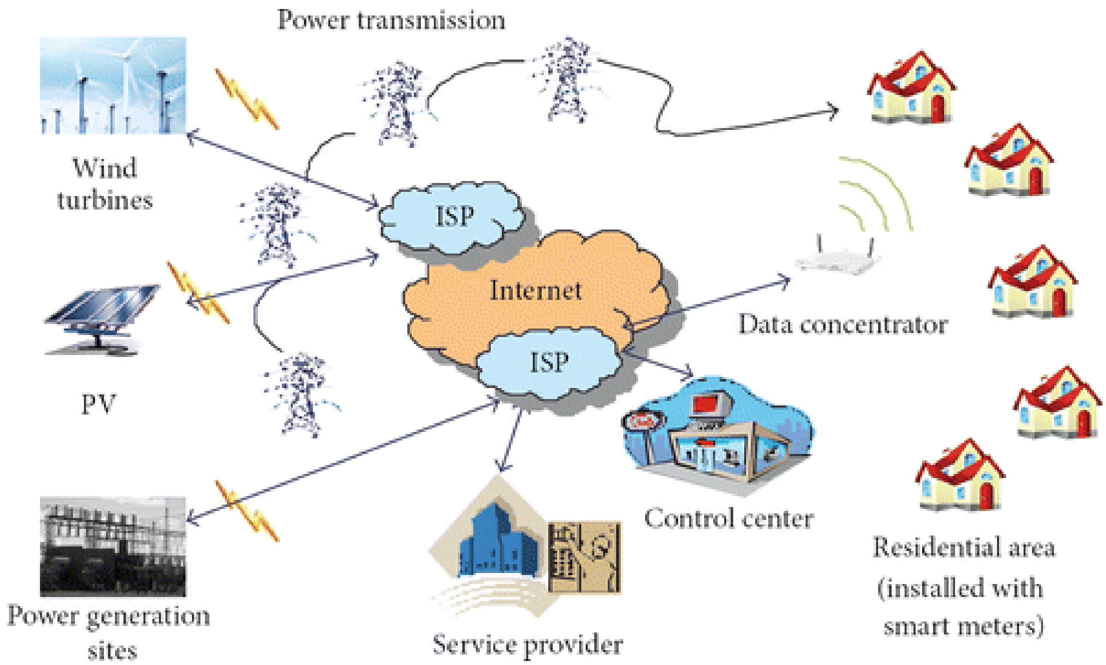

Fig. 3. An example of architecture in smart grid [76]

Some of the standers could be maximizing penetration of distributed generation, reduce peak load demand, improve economic benefits by offering rewards to the customer to voluntarily lessen the demand during high peak periods [7]-[8]. In general, a smart grid is the collection of a traditional distribution network and a bidirectional connection network for control, monitoring, and sending of information on energy consumptions. An example of architecture in a smart grid is shown in Fig.3. A typical smart grid includes of multiple power generating unites and power consuming entities, all linked through the grid. The generators unit provide the energy into the grid and consumers draw energy from the grid.

1.7 Direct Load Control (DLC)

Modern DLC plans delivered by the energy provider are generally based on the contract signing up between the customers and the utility, i.e., customers give utilities the option to control the appliances remotely by shutting down part of the load during high peak demand time or power supply contingency, thus, receive incentive on electricity cost for this participation.

These plans have been considered by many utilities, e.g., [25], [26]. Several restrictions occur for these kinds of direct load control DLC programs. First, they are only for emergency situations so that they do not fully utilize operational flexibilities of appliances to help control the power delivered and demand. Second, when the customer load is large, the design of the local control scheme used in modern DLC programs is complicated both in terms of calculation and communication infrastructure requirements. Third, another weakness of current direct load control (DLC) programs is the customers privacy matters because their power consumption profile is exposed whenever each single appliance is remotely rescheduled by a central controller.

DSM can be performed by using DLC, utility manage the customer consumption load using this method, and customers appliance can be controlled by information technology (IT) [27]. Different type of algorithms used for DLC, in [28] the author propose an optimization algorithm that can apply with either on or of time to manage and control the load in residential and industrial.

Direct Load Control (DCL) can be used to reduce the peak load for the large-scale residential demand response implantation [29], in [30] an optimization technique based on dynamic programming was used to achieve the optimal DLC strategy. Genetic algorithm used to optimize the scheduling of DCL strategies [31], and integer linear programming in [32]. Its worth to mention that in some DLC optimization algorithm used for certain appliances in a household, for example refrigerator, air conditioning [33-35], [55]. However, in our work the algorithm implemented used developed to cover a variety of appliances in different types of loads such commercial load and residential although household.

1.8 Demand Response (DR) and Load Scheduling

Users are motived to be an active participants to manage their loads by reducing their consumption at peak load hours can be the alternative of the DLC [36]-[37]. In this regard, the most common DR include critical-peak pricing (CPP), time-of-use pricing (TOUP), and real-time pricing (RTP). For example, in RTP tariffs, the price of electricity changes at different hours of the day, while the in TOUP electricity prices are previously determined and the consumer shift the operation time of the load accordingly.

In real time pricing the problem is that is difficult and confusing for the consumer to response to the variation in the price every hour and also peak load may occurs in the low-price time period [38].The peak load may cause instability in the system; therefore, it would be important to deploy TOUP price with max demand limit as block rates. In fact this what it included in the optimization scheduling technique. Several methods and studies have been implemented over the past two decades in order to minimize the electricity cost based day-head price. In [39] DLC algorithm using linear programming developed, the results show that the electricity cost charged to the customers reduced after participating in DCL program. Smart pricing adopted [40] to achieve lower electricity cost, propose a power scheduling for demand response in smart grid system, results show that the proposed scheme leads to reduce the peak demand.

In [41] proposed direct load control based on linear program algorithm to control large number of customers with controlling appliances in order to achieve maximum load reduction. Another linear program model was developed in [42] to optimize system peak demand period, load reduction in commercial area, and residential load. Heuristic based evolutionary algorithm (EA) also used for energy management in [43] applied for load scheduling for DCL based on load shifting, this algorithm easily adapts heuristic in the problem.

In our dissetration Colonial Selection Algorithm (CSA) method based on the biological immune system and the natural defense mechanism of human body. In CSA the limitation is that the quality of the results depends highly on the initial population and the probabilities of the mutation. The population size in my work makes the algorithm converge towards high quality solutions within a few generations, also its easy to implement and fast convergence. The main difference between CSA and PSO is that PSO doesnt have genetic operators such mutation, but both CSA and PSO shares one aspect thats is they have memory which means they save the last iterations and updates during the optimization process.

According to [44] PSO similar to the genetic algorithm GA as they both population-based search. Over the years an optimum solution to the problem of scheduling of household demand side management in the presence of PV generation took more attention. In [45] optimal scheduling and controlling approach has been studied which performs the scheduling of household appliances and management of local energy resources. A high penetration of distributed generation can lead to problems in low voltage distribution networks, for this a good review of the literature in [46] focused on PV penetration limit due to voltage violation in the low-level networks.

In [47] the author proposed an optimization technique base real-time demand response and renewable energy. Optimal load scheduling of households appliances and management of local resource approach assuming a rooftop solar PV.

In [63-69] researches covered optimization of the performance of the micro grid to make the best use of the renewable generation resource and to reduce the dependency on energy provider. For example, in [63] and [65] energy management system model proposed including PV generators with storage units. While in [64] the author introduces a residential PV generation energy storage system consider the pattern of daily operation load of the homeowner.

The benefit of a storage system in local residential PV installation presents in [66] and [67], the authors study the impact of PV on the quality of the low voltage network. As highlighted in [68] the proposed techniques did not considered the importance of balance between the objectives, such as energy cost minimization, peak load minimization and user comfort maximization. In another word a good DSM algorithm should have the objective that should cover the minimized the electricity cost and maximizing the consumer convenient and handle large number of appliances of several types.

In [70, 71, 72 and 73] a DMS methods based on a day -a head optimization process to reduce the user electricity bill by producing or storing energy. Ref. [74] proposes a new controller for peak load shaving and scheduling power consumption of domestic electric water heater using binary particle swarm optimization. Ref. [55] proposed load management technique for the air conditioner to enables consumer with small air conditioner appliances to participate in various load management programs such that they can be motivated by incentives from the utilities to lower their monthly electricity bills. The work in [56] smart load management is developed for coordinate the scheduling electric vehicles. In [57] and [58] the authors proposed model which aims to find the optimal starting time for charging the battery to minimize the cost delivered by the transformer.

A DSM technique to reduce the peak load of the grid proposed in [59], the idea in this technique is that the load demand provide of the user side using the smart power system and the energy provider update the energy price accordingly. The outcomes from previous researches illustrate that the daily power consumption pattern can be smother and more controlled through different DSM schemes.

Demand response scheduling under load uncertainty based on real-time pricing in a residential grid presented in [60, 61, and 62], in these references, authors used game theory to obtain the optimal load consumption pattern based on provided price, and the authors model the interaction between the energy provider and the consumer using game theory. In additional, several works proposed scheduling schemes in smart grid environment [6872], In order to improve the quality of the power grid and to enable the consumer to reshape his production and consumption pattern. For instance, [68, 69 and 70] propose an optimal residential load scheduling models using mixed integer linear programming. The proposed model also presents the integration of the renewable generation with battery storage system. The model aims to help the consumer to reschedule the appliances to get optimal benefit and to minimize the electricity bill.

The author in [70] proposed an optimal scheduling technique for residential appliances in smart home with local PV generation, Results indicate that the proposed strategy have the capability of maximizing the savings in electricity cost. The work in [71] studies scheduling of different types of appliances by adopting dynamic programming-based game theoretic approach. Its assumed that the consumers with extra power generation can choose their offered price and output generation such that they reach the maximum revenue and reduce their electricity bill.

1.9 Reason in the design of the proposed algorithm

In most of the DSM programs that have been used over the past two decades (e.g. [33], [34], [41]), the focus has been on interactions between the utility company and the consumer. Most of the proposed algorithms did not consider the importance of balance between the objectives energy cost minimization, peak load minimization and user comfort.

In this dissertation, a DSM model is proposed and mathematical models for the grid, renewable energy resource represented by rooftop PV generation are presented as well as for different type of electrical appliances in different types of loads commercial and residential. This model can effectively minimize the energy consumption cost for day-ahead time. Its worth to mention that in some DLC optimization algorithm used for certain appliances in a household, for example refrigerator, air conditioning [35]. However, in this work the algorithm implemented used developed and expanded to cover a variety of appliances in different types of loads such commercial load and residential household although they have different characteristic in terms of load profile, electricity price, appliances, and their customer willingness for DSM participation.

Unlike the work in Ref. [17], an appropriate TOUP profiles were used for both residential and commercial loads, in fact the profiles were different for each load [49]. Our algorithm takes into the regard the voltage fluctuation and the power loss of the entire system while optimize the electricity cost. The goal is to reschedule the energy consumption, considering the day-ahead dynamic electricity price and the real production of the photovoltaic system. Its worth mentioning that real time pricing the problem is that is difficult and confuse for the consumer to response to the variation in the price every hour and also peak load may occurs in the low price time period as stated in literature survey [38].The peak load may cause instability in the system; therefore, it would be important to deploy TOUP price with max demand limit as block rates.

The proposed optimization-based model also aims to reduce the total electricity bill but ensuring a comfortable user experience at home. This model can effectively minimize the energy consumption cost for day-ahead time horizon according to the forecasted electricity price, taking into the account the power loss of the system. Moreover, the proposed model implemented using Colonial Selection Algorithm (CSA) method based on the biological immune system and the natural defense mechanism of human body. In CSA the limitation is that the quality of the results depends highly on the initial population and the probabilities of the mutation. The population size in my work makes the algorithm converge towards high quality solutions within a few generations, also its easy to implement and fast convergence.

The main difference between CSA and PSO is that PSO doesnt have genetic operators such mutation, but both CSA and PSO shares one aspect thats is they have memory which means they save the last iterations and updates during the optimization process. According to [24] PSO similar to the genetic algorithm GA as they both population-based search, in PSO the memory is important to the algorithm.

To summaries and compared to other related work in the literature, this work has following key contributions: 1) the proposed DSM model incorporates economic benefits of local solar PV generation along with negative impacts on voltage fluctuations and deviation in the distribution network. It should be noted here that most reference works ignore voltage problem in the presence of photovoltaic system. 2) Propose a practical model for demand side management with a flexible penalty approach to account for the inconvenience caused by deviation from customer desired schedule. In other words, customer inconveniences caused by DSM schedule will be translated into additional compensation cost in the optimization objective function which is calculated based on some customized rate and intends to effectively discourage or reduce unnecessary load shifting or changes. Also, the work extends the single household case in our previous work [5] to that of multiple households and commercial load.

Using the developed simulation model, we evaluate the performance of decentralized DSM and study their impact on the distribution network operation and renewable integration, in terms of utilization efficiency of rooftop PV generation, voltage fluctuation and real power loss. Residential and commercial loads have different characteristics in terms of load profile, electricity price, appliances, and their customer willingness for DSM participation. In other words, using DSM strategy for residential and commercial loads does not have same impacts on electricity cost and specifically distribution network operation.

In fact, decentralized DSM especially for commercial load may have negative impacts on network operation in terms of power quality and energy loss, however, for residential decentralized DSM we can improve the network operation indexes most of the times. Therefore, it is necessary to examine DSM strategy for both commercial and residential sectors in a distribution network together and compare their performance in sense of network operation parameters and customer benefit as savings on electricity cost.

1.10 Clonal Selection Algorithm

The Artificial Immune System (AIS) is a powerful computational intelligence method based on the biological immune system and the natural defense mechanism of human body. When an antigen such as a bacterium, a virus, etc. invades the body, the biological immune system will select the antibodies which can effectively recognize and destroy the antigen. In AIS, Clonal Selection Algorithms (CSA) are a class of algorithms inspired by the Clonal selection theory which has become a widespread accepted model for how the immune system responds to infections. In the past decade CSA is widely used in power system analysis [21 - 23].

In the Clonal selection algorithm, a candidate solution for the specific problem is called an antigen, which is recognized by the antibody. Each antibody represents a possible solution to the problem. A population consists of a restricted number of antibodies. In this algorithm, after recognizing an antigen, immune system reproduces antibodies which can identify that particular antigen. Consequently, every antibody is evaluated by the evaluation mechanism to obtain its affinity. In addition, mutation process is also performed on regenerated antibodies causing partial differences between them. These differences make the population able to recognize antigens that were not recognizable for initial antibodies.

With above explanation, steps of the Clonal selection algorithm (CLONALG) can be described as follows:

1. Produce the initial population randomly in the problem space. The number of initial antibodies in the population is N.

2. Determine the affinity of each antibodies (evaluating by objective function).

3. Select n antibodies which have the highest affinity.

4. Improve new population which has n antibodies.

   Improvement is in proportion to each antibodys affinity, that is, an antibody with higher affinity will be copied more than other antibodies with lower affinity.

$$nc = round(B.N/i), \quad i = 1 \ \ to \ \ n \tag{1.1}$$

   Where nc is the number of offspring antibodies from ith antibody (parent) and is a constant coefficient which indicates the rate of copy. At the end of this step, the number of antibodies in the refreshed population would be Nc, which is defined as follows:

$$N_c = \sum_{i=1}^{n} round(B.N/i) \tag{1.2}$$

Mutate Nc antibodies of the population in proportion to their affinities, that is, antibodies with higher affinity should be mutated less than those with lower affinity.

5. Determine the affinity of each mutated antibody and select m antibodies with higher affinity. Therefore, the population consists of m antibodies which will enter the next generation directly.

6. Generate p new antibodies randomly and add them to the population. These new antibodies increase the solution diversity and consequently the optimization process would be able to escape from the local optima. This step causes the number of antibodies in the final population to reach (m+p).

7. Return back to step 2 and repeat this cycle until the termination criteria are met.

1.11 Simulation Parameters

Prices change based on the day as well as the time of day. During the summer, the highest prices are in the middle of the day between 1 and 7 PM, during the winter the highest prices are during the early morning and late at night. Each day classified as a high priced day (A Day), a medium priced day (B Day) or a low priced day (C

Day). Low priced (C) days will occur most frequently, at least 280 days a year. There will be no more than 30 high-priced (A) days per year Dominion provides notification in advance for high priced days by 6 PM the day before.

For simulations, a day is divided into 48 time slots (0.5 hour per slot). Smart pricing plan-day classification calendar data is adopted from Dominion Virginia Power (August 17, 2015) [24]. As depicted in Figure .2.1. The output generation profiles are also obtained by scaling down the typical solar [25]-[26].

In order to have an actual price signal in our simulation, we add a white noise to the historical price data. The mentioned white noise follows a normal distribution It is assumed sixteen types of schedulable domestic appliances in the home these are [13]:

1. Baseline appliances: it is the must-run service that needs to be served immediately when it is requested by the residents, e.g. lighting, fridge, television.

2. Uninterruptible appliances: it refers to the domestic appliances (e.g. rice cooker, dish washer washing machine) that require to be operated continuously until completion of the task.

3. Interruptible appliances: it refers to the appliances which can run and can be shut down at any time .In this table as we can see that for some appliances it is assumed a multiple period, consumer in this case has more than one time duration to turn on the appliance.

A-Cooling Season: beginning April 16 and extending through October 15.		
Day Classification	Time Period	Rate per ES kWh
A	1 p.m. to 7 p.m. 10 AM to 1 PM& 7 PM to 10 PM All other hours	44.331¢ 8.091¢ 2.365¢
B	10 AM to PM All other hours	5.184¢ 1.290¢
C	10 AM to 10 PM All other hours	2.431¢ 0.305¢

B. Heating Season: period beginning October 16 and extending through April 15.		
Day Classification	Time Period	Rate per ES kWh
A	5 AM to 11AM. & 5 PM to 10 PM All other hours	27.439¢ 4.775¢
B	5 AM to 11 AM & 5 PM to 10 PM All other hours	5.268¢ 2.872¢
C	5 AM to 11 AM & 5 PM to 10 PM All other hours	2.313¢ 0.87¢

CHAPTER 2

LOAD SCHEDULING WITH MAXIMUM DEMAND AND TIME OF USE PRICING FOR MICROGRIDS

2.1 Introduction

Along with distribution networks, modern communication infrastructures have also begun to be installed, in order to support and improve the reliability and efficiency of the power networks [1]. In this new electricity network, a large number of data sets are available for residential consumers to improve the energy consumption policies, by means of changing their habits in using household appliances [2]. They even can sell their excess energy from renewables to the grid using a smart energy management system like the one proposed in [3]. In order to evaluate the effectiveness of an energy management system, electricity demand needs to be analyzed in a high-resolution fashion [3]. This is required in order to identify which type of electricity activities can be modified without any weighty impact on the consumers lifestyle and freedom [4]-[5].

During the last decade, various models have been proposed to define household demand side management strategies for improving the performance of the distribution networks. But the focuses and contributions of the models tends to be different. Reference [6], proposed a model that based on devices future usage, the consumer is able to optimally schedule home appliances activities for the next day and with the goal of minimizing the electricity bill.

In [7]-[8], real-time monitoring system is presented as an effective way to improve the efficiency of different control methods in the energy management system.

This model provides a great potential to control the activities of appliances especially the indoor temperature control devices. However, the real-time electricity price is usually ignored for this type of methods. In reference [9], the design of a genetic algorithm-based control method is presented in order to reduce the electricity bill but considering user freedom at home.

According to the results presented in [9], this method can reduce the total electricity cost considering the real-time monitoring system and the electricity price. In reference [10], the authors utilized the concept of teletraffic theory to reflect the characteristics of electricity consumption. This framework can be used to compare and evaluate different demand side management approaches. Regarding the impact of renewable energy resources, many research works have been carried out in the literature.

A high penetration of distributed generation can lead to problems in low voltage distribution networks. For example, in residential areas with a high level penetration of installed photovoltaic generation, situations occur when the power flow reverses and the total generation of PV system exceed the peak load. In [11], the authors proposed an active DSM model to address issues of integration of renewable energy resources in distribution networks. Reference [12] provided a mathematical definition for electricity generation optimization in a typical residential load with different energy systems. This reference deals with an economical electricity storage system to optimize simultaneously the electric shiftable loads.

The objective of this chapter is to set up an optimization model for the offline household demand side management. The goal is to reschedule the energy consumption, taking into account the day-ahead dynamic electricity price and the real production of the photovoltaic system. The proposed optimization-based model aims to reduce the total electricity bill but ensuring a comfortable user experience at home.

This model can effectively minimize the energy consumption cost for day-ahead time horizon according to the forecasted electricity price. Compared to the existing work, the key contributions made in this work can be summarized as follows:

1. This work deals with the economic benefits of PV system along with its negative effect on voltage deviation in the distribution feeder. It should be noted here that the most of the references ignore the voltage stability in the presence of photovoltaic system.

2. This work proposes a practical model for demand side management based on penalty approach. In this model the deviation from the desired schedule will be penalized based on the market price or a relatively larger value that can effectively prevent and/or reduce deviations.

2.2 System Model and Mathmatical Formulation

In this Section, we set up a physical and mathematical model to show the architecture of household demand side management system.

2.2.1 System Model

Figure 4 illustrates the architecture of system model for a residential smart home including PV panels and a set of active appliances under a real-time pricing environment. This model contains a single line feeder with thirteen buses. We assume that a mid-size smart home is located at the end of the feeder and equipped with a 4.5 kW PV panel. It should be noted here that all the household electric devices can be controlled in order to minimize the energy consumption.

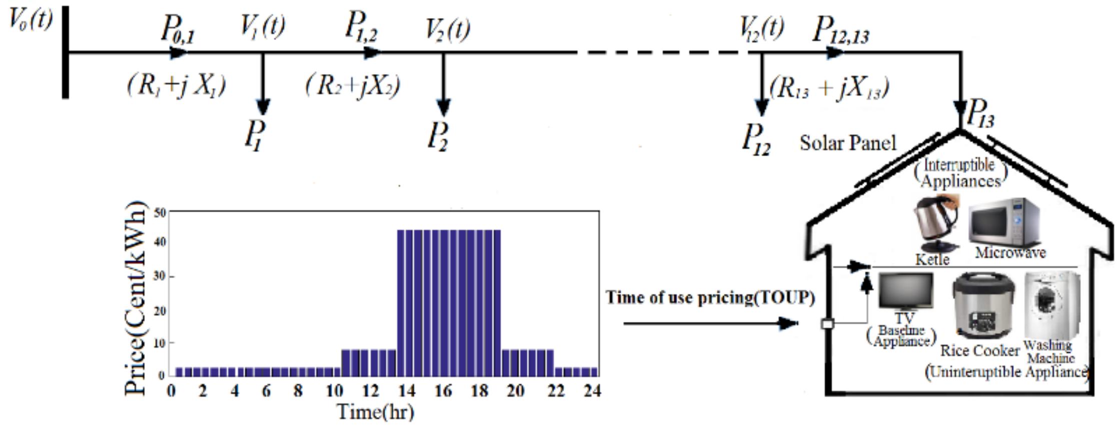

Fig. 4. Hybrid system layout for a single house scenario

In this model we intend to consider the most widespread used appliances that are categorized into three different types based on their operational futures: 1) Interruptible appliances: it refers to the electric devices which are allowed to operate and can be shut down at any time; 2) Uninterruptible appliances: it refers to electric devices that need to be operated continually; and 3) baseline appliances: this type of appliances should be active for entire simulation time (24 hour). It is assumed that all the appliances need to meet the operational limits and operate at specific power rating.

Although the proposed DSM model approximates a constant power rating for each appliance, this can be easily enhanced to simulate appliances that exhibit non-linear power usage, given the availability of such detailed load profile data. Note that in reality each household has a specific set of electric devices, with different power ratings and operational features, while the proposed model assumes a certain homogeneity between household appliances to make the configuration more reasonable.

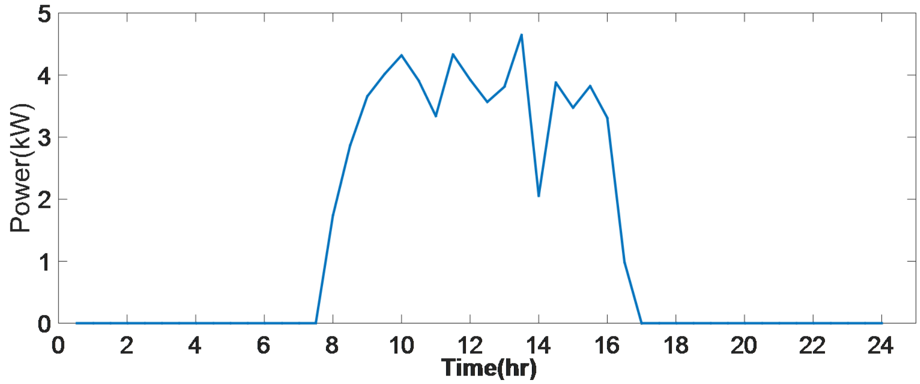

Fig. 5. Photovoltaic system generation

2.2.2 Duration of operation

For all simulations, a day is divided into 48 time slots which are represented by their starting times. The starting slot over the whole day is 00:00 A.M and the ending slot is 11:30 P.M. For each appliance, there is a specific operation time which is presented by a minimum starting time and a maximum ending time. The end-user is free to operate each appliance on any time as long as he/she respects the constraint of starting and ending times.

2.2.3 Photovoltaic System

A typical micro-grid for residential homes integrates the operation of different type of energy sources and demand. This work considers a 4.5 kW rooftop PV panel with off-grid connection to distribution feeder. Off-grid connection means that during any time if the output of the rooftop PV system is more than the expected demand, the extra electricity will not be exported to grid, but we can save it by using the energy storage system. Fig. 5 shows the power profile of a typical 4.5 kW rooftop panel.

2.3 Problem Formulation

The proposed household DSM model is aimed at minimizing the electricity cost by switching on/off domestic appliances over the operational periods, considering the varying electricity price. In the concept of smart home operation, the focus is on the best decision to be taken for given short-term, say one day, operating condition. Thus, the operation costs of the PV rooftop system is negligible during the time simulation, and making the best use of the rooftop PV system can dramatically reduce the purchase of electricity from the grid. In the case that the total load is less than PV generation, no electricity purchase is required. However, for higher total load the economical purchase of the electricity is needed. This procedure can be modeled as an optimization problem which is presented as follows:

min $\mathrm{C}_e + C_p$

$[\mathrm{u}_a(t)]$

Subject to:

$$\underset{e}{C} = 0.5 \times \sum_{t=1}^{T} P_{load}(t)\pi_e(t) \tag{2.1}$$

$$C_p = 0.5 \times \sum_{a=1}^{A} \pi_p \cdot r_a \cdot \Delta T_a \tag{2.2}$$

$$p_{load}(t) = \max((\sum_{a=1}^{A} r_a \times u_a(t) - \alpha \cdot p_{pv}(t)),\, 0) \tag{2.3}$$

$$\sum_{a=1}^{A} r_a \times u_a(t) \leq MD \qquad \forall\ a \in \{1\ to\ A\} \tag{2.4}$$

$$\sum_{t=1}^{T} u_a(t) = D_a \qquad \forall\ a \in \{1\ to\ A\} \tag{2.5}$$

$$u_a(t) = 0 \qquad \forall\ t < S_a \quad or \quad \forall\ t > \ f_a \tag{2.6}$$

$$\Delta T_a = 1^T \cdot |t_a^{st_{new}} \ - t_a^{st_{old}}| \qquad \forall\ a \in \{1\ to\ A\} \tag{2.7}$$

$$t_a^{st_{new}} = [t|u_a^{new}(t) = 1]_{1 \times D_a} \qquad \forall\ a \in \{1\ to\ A\} \tag{2.8}$$

$$t_a^{st_{old}} = [t|u_a^{old}(t) = 1]_{1 \times D_a} \qquad \forall\ a \in \{1\ to\ A\} \tag{2.9}$$

$$[v(t)] = f_{AC}\ (P_g(t),\ P_g^{PV}(t),\ P_L^*(t)\ |\ Y_{bus}) \tag{2.10}$$

$$E_{loss} = \sum_{t=1}^{T} \sum_{l=1}^{L} |\ i_L^{\,t}\ |^2\ R_L \tag{2.11}$$

$$\sigma_v = \sqrt{\frac{1}{TN} \sum_{t=1}^{T} \sum_{i=1}^{N} (v_i^t - \overline{v})^2} \tag{2.12}$$

u_a is the operation status of the appliance a; its 0 when the appliance is off, and 1 when it ON, with following format:

$[u_a(t)]_{A \times T} = [u_1^1,\ u_1^2, ..., \ u_1^T;\ u_1^1,\ u_2^2, ...,\ u_2^T; ....;\ u_A^1,\ u_A^2, ...,\ u_A^T]$

$minC_e + C_P$:Minimize electricity cost penalty price Over a 24h (30 min per slot) period

Constraints

Eq. 2.3 : Avoid negative electricity cost

Eq. 2.4 : Maximum Demand (MD) constraint

2.5 and 2.6 : Total operation duration and the allowable turnon time of appliances

Eq. 2.7 : calclute the long shit.

Eq. 2.8 and 2.9: the original and the new starting point for duration of timeshifting for flexible appliances

Eq. 2.10: voltage constraint in the distribution network. using power flow calculation.

Eq. 2.11: calculate the energy lost .

Eq. 2.12: to calculate the voltage fluctuation.

u_a Binary status of appliance a; 0 = off, 1 = on

It is worth to mention here that in the simulation the run time cost is negligible and PV cost is static.

Where:

U_a :The operation status of the appliance a; ON/OFF

r_a: Power in kW for appliance .

A : Interruptible and uninterruptible number.

A: The appliances number.

T : number of the time slots, T= 48 slots each slots of 30 minutes.

t : Index refer to the time slot.

D_a: Time duration of each appliance.

S_a, f_a: The possible starting and ending time slot for each appliance.

$t_a^{st_{new}}$: Refers to the New Time slot after apply DSM.

$t_a^{st_{old}}$: Refers to the Old time slot befor DSM .

$p_{pv}(t)$: Refers to the Power generated by the solar PV.

$\pi_e(t)$:Time-of Use Pricing .

π_p: Penalty price in Cent.

ΔT_a:Refers to the number of the slots shifted after apply DSM.

MD: Refers to the threshold of the energy usage.

C_e: Refer to the energy usage cost.

It means that for a typical interruptible appliance, as illustrated in Figure 2.4 , there is no the uniform value of time-shifting for all operation time slots, and in order to have a fair comparison, each time slot should be treated individually. Normally when there is no shift the penalty cost is zero ($C_p = 0\,\$/\text{day}$) which means there is no time shifting slots for the operated appliances and ($\Delta T_a = t_{a,m}^{st_{new}} - t_{a,m}^{st_{old}} = 0$), in this case consume has to pay for the consumed energy kW/h as electricity C_e based on the TOUP.

With optimal shifting the total cost that consumer has to pay will reduced due to the cost saving (C_{saving}) in c/kWh that comes after shift the operation time from high price to low price period, in this case consumer will pay extra cost as penalty cost. Its important to mention that the algorithm make shift whenever there is cost saving in another world ($C_{saving} > C_p$) and the total cost paid by consumer is ($C_e - C_{saving} + C_p$).

(7)- (9) represent the distribution network constraints of AC power flow balance and real power loss and to avoid the violation may happen in the distribution network. We impose a 5% limit on each bus, in another word node voltages should be in their normal limit (+/- 5%). Power loss is due to the high of resistance of the line and the load at the bus, both are contribute to the total power loss of the system. The math representation of the P$_loss(t)$:

$P_{loss} = \sum_{i=1}^{n_{br}} |I_i|^2 r_i$ (2.13)

Where n_{br} : number of nodes in the feeder, $|I_i|$: is the node current, r_i is the resistance.

2.3.1 Algorithm Steps for Adding Penalty Part

We have U as optimization variables

Let $U^0 = [u_j^0(t)]_(mt)$, where U^0 represents our starting benchmark

In fact $u_j^0(t)$ denotes whiter the appliance j is on or at off state.So, $([u_j^0(t)]_(mt))$ represents a binary matrix.

Let v denotes the iteration step, which means we optimized U for each step. And for each iteration step we need to optimize U to get $u_j^v(t)$ after v iteration step.

In order to evaluate the time shift for each appliance.

1- Compare $(u_j^0(t))$ with $u_j^v(t)$. To have a fair comparison each operation time slot treated individually. To do that we need to define an operating time vector for the j$^t happlianceT_j$.

T$_j^0$ $= [t|u_j^0(t) = 1]_(l_j 1)$, here we need to find out the staring time slots that equal to one and put them in sequential order, where l_j denotes the duration of operating states of the jth appliance.

2- After v iteration step the final staring time slots for the jth appliance will be:

$$T_j^v = [t|u_j^v(t) = 1]_(l_j 1)$$

3- Compute T_j , which represent the difference between T_j^0 and T_j^v

T_j= $1^T.|T_j^0 - T_j^v|$

From the last equation above we conclude that:

A) For inflexible appliances we have all the time slots equal to one, so that T_j will always equal to zero, which means no penalty added in this case.

B) For uninterruptible appliances we will have l_j of time slots continuously and

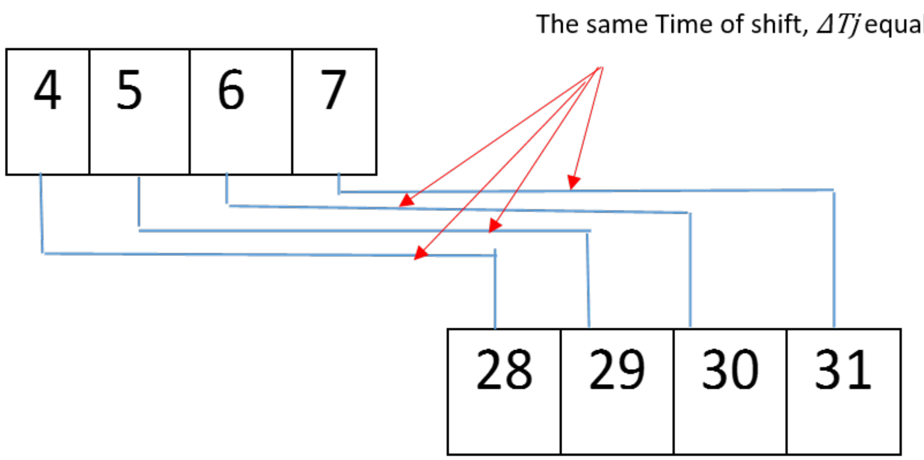

Fig. 6. Example of Uninterruptible appliances

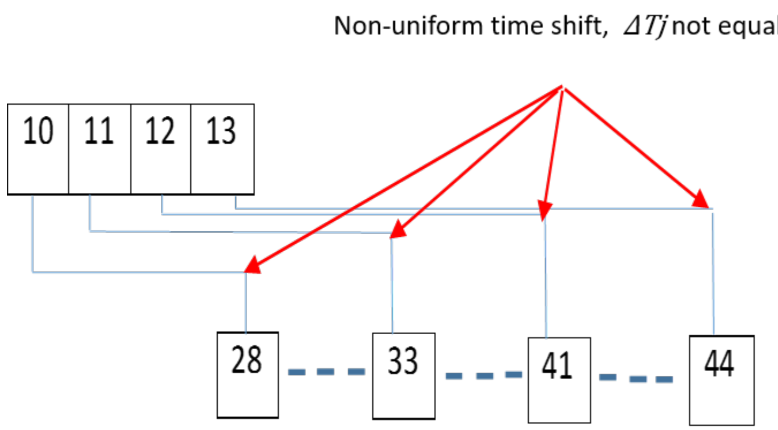

Fig. 7. Example of Interruptible appliances

$|T_j^0 - T_j^v|$ will be an even shift, which has the same time of shift.See Fig 6 C) For interruptible appliances we will have $l_j of time slots noncontinuous, and —$ $T_j^0 - T_j^v|$ will be non-uniform time shift, T_j not equal. See Fig.7

The aforementioned DSM optimization model will not simply move the operation times from peak-hours to off-peak time slots to save the electricity cost. A penalty cost included in the objective function (2) takes into account the customer willingness to change the appliances operation time. This means to discourage unnecessary load shifting that only causes small reduction in electricity cost (C_e) than the increase from inconvenience-penalty cost (C_p).

A heuristic algorithm called Clonal Selection Algorithm (CSA) is adopted to find the optimal operation schedule for the household appliances. The CSA is a powerful computational algorithm based on the biological immune system and the natural defense mechanism of human body. This method considers each candidate solution and its distance from global optimal solution, as an antibody and an antigen, respectively. The affinity of every single antibody is calculated via evaluation mechanism and then, they are sorted based on their affinity values. Finally, a new enhanced population is generated using immune operators [14]. In DSM problem, the optimal solution of this algorithm will determine the minimum total cost of electricity and time-shifting penalty, achieved with an optimal schedule $[u_a(t)]_(AT)$ which represents operation status of each appliance at each time slot.

It should be noted that the optimization process, presented above, is not simply moving the operation times to some specific time slots with lower electricity price. In fact, implementation of the DSM would solve the aforementioned optimization problem that electricity consumers face, however, in order to work reliably, it is necessary that the DSM system schedules the appliances based on the desired (original) operational times. Therefore, all deviations from the desired schedule will be penalized based on the market price or a relatively larger value that can effectively prevent and/or reduce deviations. In this paper, it is assumed that the penalty will be applied when the deviation is positive, i.e., the decline in the electricity price after moving the operating time. Negative deviation will not be penalized in our proposed model. This issue is further investigated in numerical results.

In this paper, Clonal Selection Algorithm CSA is adopted to find the optimal operation time for household appliances. The results of this algorithm contain the total operation cost and the optimal schedule $[u(t)]_(tm)$ which represents operation times and power consumptions.

See the flow char of the CSA PROCESS

Algorithm 1: PV-based demand scheduling Required: MD, M, $_{0}, _{c}, P_pv, r, R, l,$ T^o,T^v,t

1: Initialization: $Iteration_Max$, Pop size, , mt

2: Gen, $U_0 = u_a(t)$ Original schedule

3: Check technical constraints

4: Gen initial population $u_a(t)$, Shifting the time slots

5: Check technical constraints

6: FOR i= 1 to Iteration$_{Max}$ DO

$7: FOR\, j = 1\; to\, Popsize\, DO.$

$8: Calculate fitness value$

$9: ENDFOR$

$10: Sort\, candidate\, schedules\, based\, on\, fitness\, values$

$11: Copy\, sorted\, candidate\, schedules$

$12: IF\, rand(0, 1) < mt$

$13: Mutate\, some\, candidate\, schedules$

$14: End\, If$

$15: Gen\, new$u$_a(t)$, add to the mutated candidates

16: Calculate fitness value

17: Sort candidate schedules

18: Select the best schedules

19: END FOR

2.4 Numerical Results

The main purpose of this part is to investigate the performance of the proposed household DSM model in terms of cost and the effect of PV generation on voltage deviation. In this section, the proposed approach is tested on three different scenarios, each with different type of setting. Figure 2.7 shows the forecasted electricity price data, adopted from Dominion Virginia Power [13], and PV generation from 6 kW roof-top photovoltaic system. For all simulation a mid-size home is considered with the major electricity consuming appliances such as washing machine, dish washer, water heater and air conditioner. It is assumed that the number of controllable and baseload appliances are up to 27 and 4, respectively. Each individual appliance is modeled using four parameters: $s_{(}j,)$ f_j, l_j and r_j, where $[s_{(}j,)f_j]$ shows the possible operating time during which the appliance j may be switched on, $s_{(}j)$,f_j denote the starting and the ending of the possible operating range respectively, r_j and l_j denote the power rating and the operating cycle time, respectively .The detailed operational futures are presented in [14].

The simulation consists three different scenarios, not all of them necessarily unique. In the first scenario DSM model is considered without PV generation and penalty. The second scenario can optimally determine the best schedule in the presence of PV generation. And in the last scenario we investigate the impact of penalty factor in DSM optimization problem.

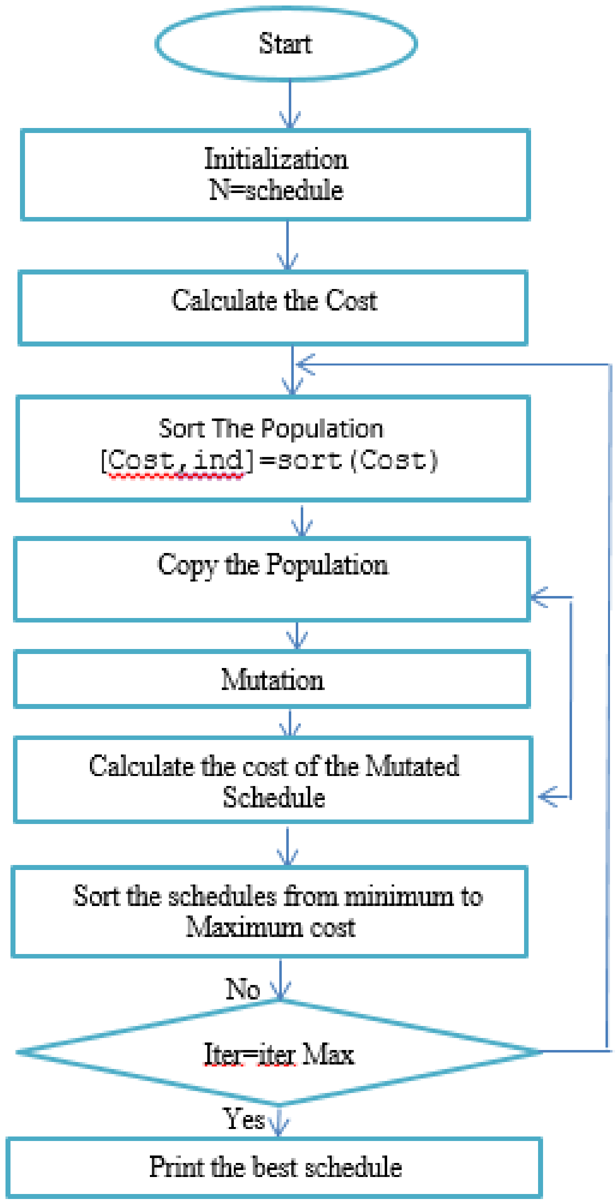

Fig. 8. Overview of the Tasks and workflow of CSA

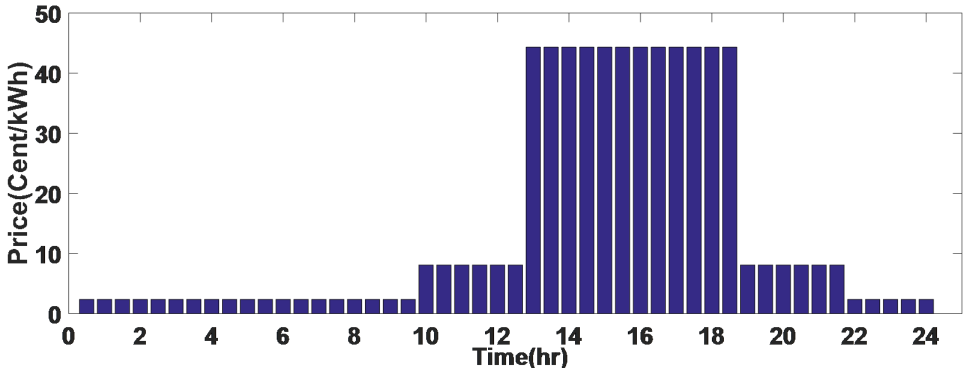

Fig. 9. Time of use pricing (TOUP) profile

2.4.1 First scenario (DSM without PV and Penalty Factor)

In this scenario, the proposed DSM approach takes into account forecasted day-ahead hourly electricity price and user preferences. Figure 10 shows the demand profile without any optimal scheduling approach (original profile). Its assumed that the consumer decides the usage of electrical appliances only according to his/her preference without any sacrifice of convenience. Fig. 6 illustrates the power drawn from the grid, in case no PV generation is set to the household.

As Figure 11 shows, the DSM allocates the domestic appliances to the least-price slots causing peaks to emerge early in the morning and end of the day. Then, a hard operation time is considered to be active from 2:00 A.M. to 8:00 A.M., and 10:00 P.M. to 12:00 P.M. in which the electricity prices are the lowest. In order to show the economic benefit of the proposed DSM approach, the operation cost is also calculated for day-ahead horizon time. From the obtained results we can see that the daily operation cost is dramatically reduced from ($12.58/day)*to*($8.21/*day*).

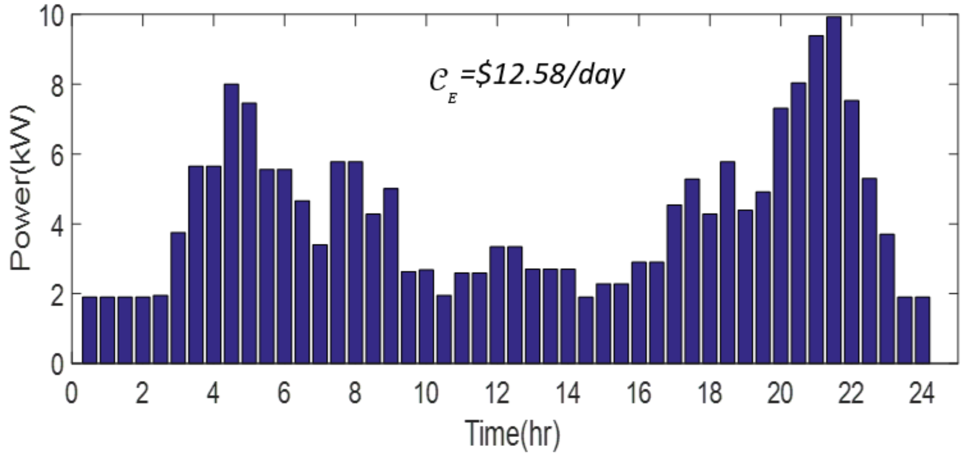

Fig. 10. Original Load profile without DSM

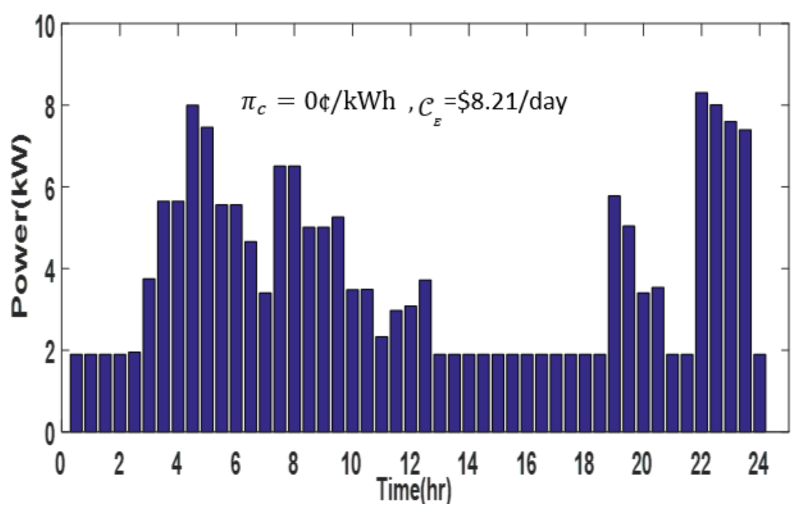

Fig. 11. Load profile with DSM (No PV, No penalty)

2.4.2 Second scenario (DSM with Penalty factor))

As stated in section II, deviations from the desired schedule will be penalized based on the market price or a relatively larger value that can effectively prevent and/or reduce deviations. The deviation cost is the penalty imposed on the objective function in case the operation time deviates from the original (desired) schedule. In the third scenario, the obtained results show the impact of different penalty fee on the DSM optimization. Technically, if the profit resulted from time-shifting becomes higher than expected penalty value, the suggested change in the user schedule will be accepted (otherwise rejected).

Fig. 12 shows the impact of different penalty values on DSM optimization. This figure plots the load profile for $\pi_p = 0, 5 and 10$ c/kWh) . As we can see, for $\pi_p = 5$ c/kWh), the final load profile has some considerable difference with Figure 2. 8 (original profile), especially for the time slots between 12:00 pm and 6:00 pm. However, when we increase the value of penalty to $\pi_p = 25$ c/kWh) or higher, we can see minimum deviation in the original schedule. This comes from the fact that for any shifting in the operation time the expected profit is less than deviation cost.

2.4.3 Third scenario (DSM with PV and Penalty factor)))

In this scenario, the effect of local electricity generation is studied through installation of 4kW PV rooftop system. It should be highlighted here that when there is enough PV generation the energy consumption is supplied entirely by photovoltaic system. However, for higher energy consumption, electricity is drowned from the grid. In this scenario, the PV panel is capable of charging the smart house during the period from 9:00 A.M to 3:00 P.M.

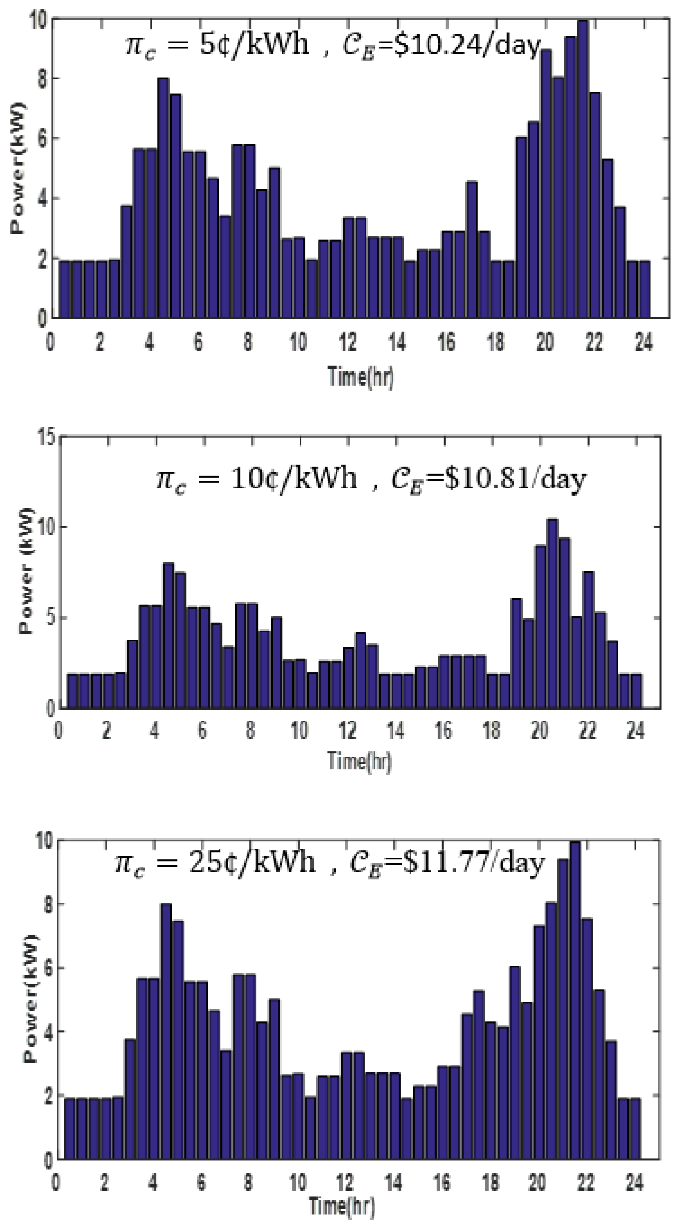

Fig. 12. Load profiles for different penalty values with DSM (No PV))

Fig.13 and 14 illustrate the load and cost profile, respectively, in the presence of PV system. From Fig.13, one can easily figure out that if we take the effect of photovoltaic system, the imported power from the grid decreased and the PV-DSM can effectively reduce the peak load and provide a great economic benefit for end-user. The obtained results show that the daily operation cost is reduced from $8.21/day*to*$4.18/*day* showing a reduction of 49 %. It is worth noting that at 2:00 pm (slot 14) in Fig. 13, the photovoltaic generation decreased to 2.0538 kW, while the load at 2:00 pm was 2.7 Kw, in this we have 0.6462 kW will not covered by the solar generation and by multiplying this reaming load by the price at this time which is 44.331/kWh the cost will be 28.646/kWh as it shown in Figure 2.12 at slot 14.

Fig. 15 and 16 illustrate the impact of installed PV system on voltage at connection point and along the distribution feeder. In these figures, we can also see a boost in voltage level along the feeder around noon which delivers a smoother voltage profile and improves voltage quality. Fig.17 shows the impact of different penalty values on DSM optimization. As we can see, for $\pi_p = 5$ c/kWh the final load profile has some difference with Fig. 12. However, when we increase the value of penalty to $\pi_p = 0$ c/kWh or higher, we can see minimum deviation in the original schedule. Table 2.1 illustrates the summary of obtained results.

Due to the small number of distributed loads connected along the single line feeder considered in this work, constraints (5) and (6) tend to be ineffective in the objective function, and the voltage maintained in the safe voltage zone, as this is depicted in Fig. 15 and 16.

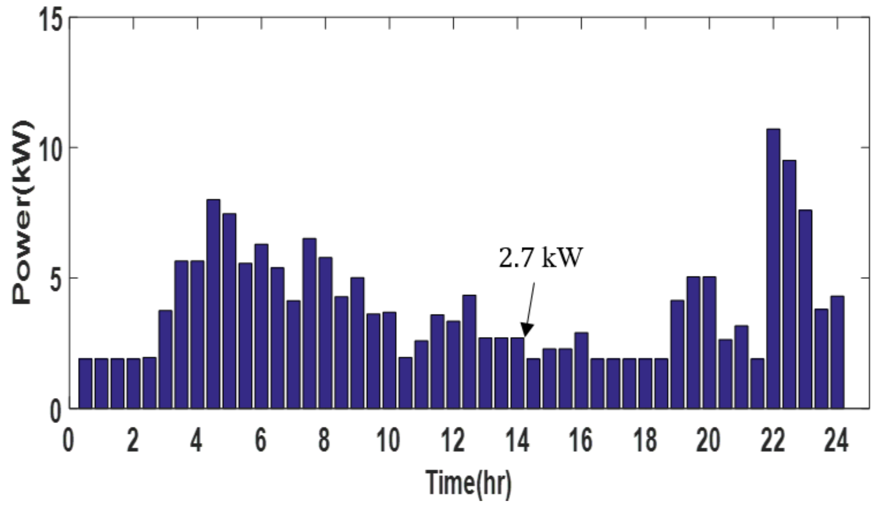

Fig. 13. Cost profile with DSM (with PV, No Penalty))

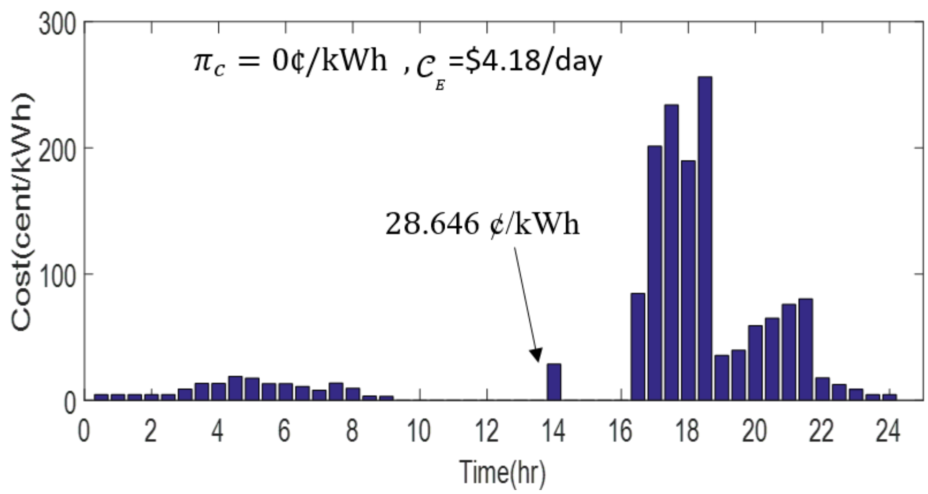

Fig. 14. Load profile with DSM (with PV, No Penalty)

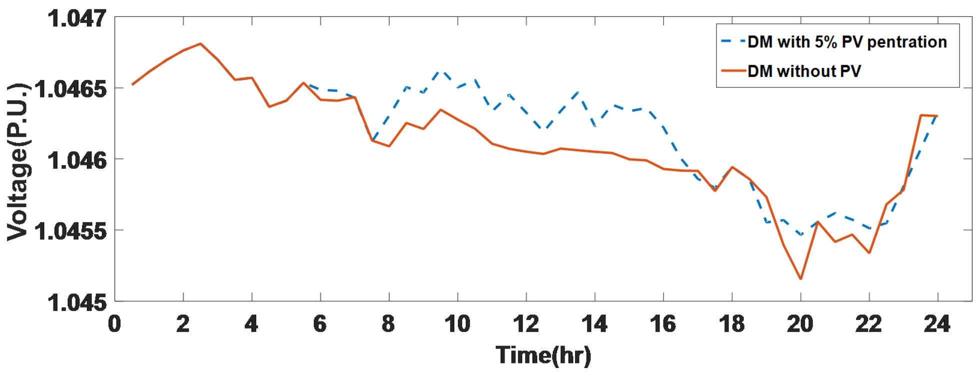

Fig. 15. Voltage profile at connection point with DSM

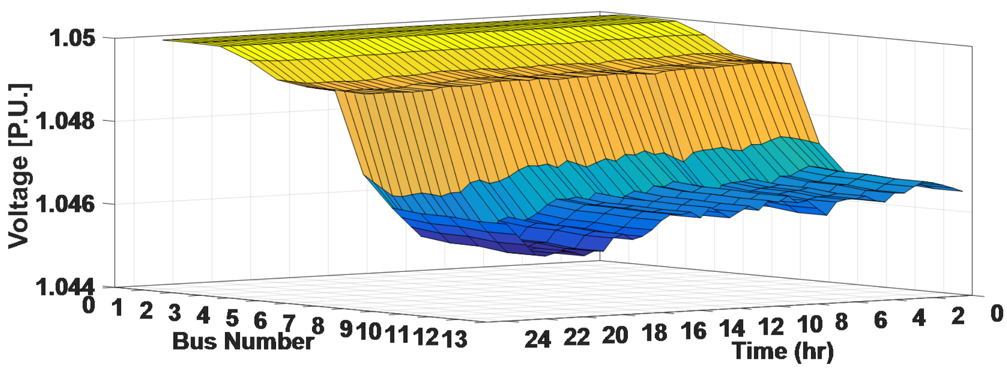

Fig. 16. Voltage profile along distribution feeder with DSM and PV

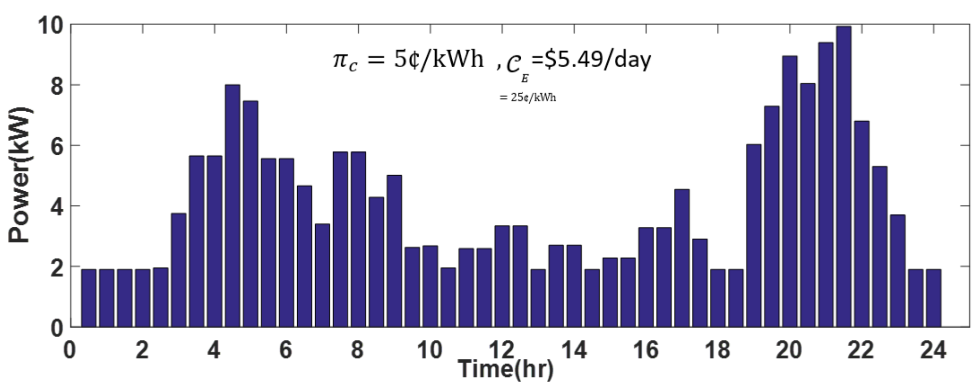

Fig. 17. Load profiles for different penalty values

Table 2.1: Comparison of Costs for the three Scenarios

Scenario#	π_c (¢/kWh)	Total Cost [\$/day]	$\mathcal{C}_E$ [\$/day]	$\mathcal{C}_c$ [¢/day]
A) DSM without PV	**0**	**8.21**	**8.21**	**0**
B) DSM (with Penalty factor, No PV)	**0**	**8.21**	**8.21**	**0**
	5	**10.58**	**10.24**	**34**
	10	**11.21**	**10.81**	**40**
	25	**12.03**	**11.77**	**26**
	50	**12.58**	**12.58**	**0**
C) DSM with 5%PV penetration and Penalty factor	**0**	**4.18**	**4.18**	**0**
	5	**5.86**	**5.49**	**37**
	10	**6.51**	**6.13**	**38**
	25	**7.38**	**7.12**	**26**

2.5 Conclusion

In this chapter, an approach has been presented for demand side management in smart residential homes. We first introduce the architecture of DSM in residential areas and then provide a practical approach for optimal operation time scheduling. Our numerical results show that an effective demand side management provides benefits not only to the end users but also to the utilities by reducing the peak load demand and overall cost.

Our proposed approach can be used in demand side management systems to help household owners to automatically create optimal load operation schedules based on comfort settings and in the presence of a PV rooftop system and dynamic electricity pricing. In this chapter, we just consider a single photovoltaic system connected to the end of the feeder. In the future further experiments and verification on other realistic distribution networks and based on distributed PV generation will be performed.

CHAPTER 3

PHOTOVOLTAIC LOCATION TEST OF AN OFF-GRID RENEWABLE SYSTEM USED FOR TYPICAL RESIDENTIAL HOUSEHOLDS

3.1 Introduction

This chapter aims to present an approach for demand side management for a group of residential homes which can be used in response to day-ahead electricity price signal, and to maximize the usage of the power generated. This task is a dual-scenario case study of four households that are participants in a DSM program on a single feeder line. In the first scenario, each of the four households has local PV generation.

In the second scenario, PV generation is provided only by other non-participant households on the same feeder.

Simulation results confirm that the proposed scheduling algorithm can effectively reflect and affect users energy consumption behavior and achieve the optimal time of electricity usage. For practical consideration, we have also taken into consideration the impact of PV generation on the total electricity cost. Analysis shows that application of higher penalty factors can significantly improve the PV utilization efficiency while reducing fluctuations in the voltage profile for the entire system. The impact of applying a DSM algorithm on the total power losses of the feeder is also studied in this chapter. The proposed solution is implemented based on the Clonal Selection Algorithm (CSA).

Demand side management (DSM) aims to efficiently manage electrical power consumption by engaging energy customers, through offering incentives and price-based signals to alter their consumption patterns or through directly controlling their loads [1]. Recently, residential DSM has attracted significant attention among DSM researchers [3-10]. Reference [5] proposed a scheduling approach of operation and energy consumption of various electrical appliances in a grid connected smart home system. Reference [6] developed a multi-household simulation framework to study decentralized DSM in a residential distribution network.

In [7], a coordinated algorithm is proposed to minimize electricity cost, and controls both household load and distributed energy resources. Reference [8] proposed a DSM strategy for three different demand classes: residential, commercial, and industrial. A new optimization technique using a simple linear programming algorithm was used to minimize the energy cost based on real-time demand response and renewable energy resources in [9].

Generally, many researchers focused on the household DSM, but neglected PV utilization efficiency, maximum demand limits, and customer welfare. Some other load-scheduling schemes used for scheduling residential loads consumption were proposed in [12]. [13] Used the combination of DSM and time-of-use (TOU) tariffs to significantly decrease the cost of energy with a high utilization of PV generation power. However, the purpose of the DSM is not only lower the electricity cost, but also to avoid the peak load even in lower energy cost periods. Therefore, in our work, a combination of time-of-use pricing (TOUP) with a fixed threshold of load consumption was applied to two types of load: residential and commercial.

A heuristicbased load scheduling scheme was proposed in [14] and [15]. These references present a demand side management strategy based on load shifting techniques for residential, commercial, and industrial services. However, neither voltage fluctuations nor voltage limitation were considered. In other words, a good DSM algorithm must have the objective of minimizing electricity costs and maximizing consumer convenience while handling a wide variety of appliances. Also, the focus of most DSM programs (e.g., [16], [17], and [18]), has been on interactions between the utility company and the consumer.

The proposed algorithms do not consider the importance of balance between the objectives of energy cost minimization, peak load minimization and user comfort. In this work, we propose a DSM algorithm, and mathematical models for the grid and for renewable energy resources represented by rooftop PV generation as well as for different type of electrical appliances in different types of residential loads.

This algorithm can effectively minimize the energy consumption cost for day-ahead time. While some other algorithms such as [19] or [20] are specific to particular appliances in the household, our algorithm can be expanded to cover a variety of appliances.

3.2 System Overview

This section describs the system model of the proposed distributed residential demand management. To show the impact of proposed DSM on multiple housholds with more diversified combinations of appliances, we consider residential loads over a radial distribution network with a set of households. There are total of four participated housholds the line feeder.Table 3.1 summarised the number of the interruptible and uninteruptible appliances in each houshold with the aggreed maximum demand (MD).

Fig. 18-A illustrates the eletric price tarrif , while B illusterates the PV genreate power considered in the simulaton. Household appliances can be classified into three types: interruptible, baseline, and uninterruptible appliances. More details and definitions of each type of households can be found in our previous paper [4]. As we

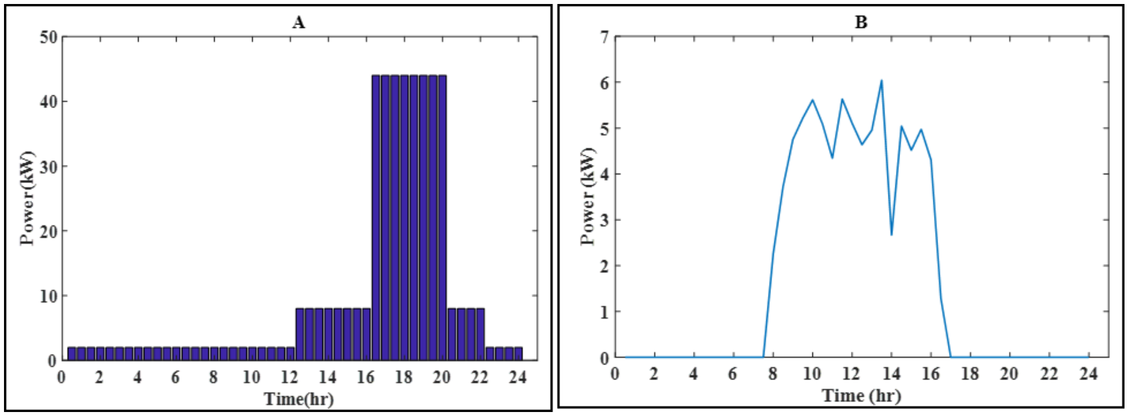

Fig. 18. A) Electricity Price signal (/kWh). B) Photovoltaic system generation

Table3.1: No. of appliances in each household with the agreed MD

Household Index	Interruptible Appliance No	Uninterruptible Appliance No.	MD(kW)
1	21	7	12.4
2	15	4	15.3
3	17	4	11.8
4	12	4	8

mentioned, four households in the line feeder with different capacities of appliances under a real-time pricing enviroment are chosen to test our model as depicted in Table 3.1. $u_(a, m)$ Represents a binary status of appliance a; $0 =$ off, $1 =$ on at Household m, with following format:

$[u_(a, m)(t)]_(AT) = [u_1^1, u_1^2, , u_1^T; u_2^1, u_2^2, u_2^T; ..; u_A^1, u_A^2, ..., u_A^T]$ (1) Where T is total number of time slots (T=48), and t is the index of the time slots. Each appliance is modeled using four parameters s_a,f_a,r_a and D$_a, where[$s$_(am,)f_(a, m)]$ defines the allowable operating time during which the appliance a in the household m may be switched on, and $r_(a, m)$ and $D_(a, m)$ denote the power rating and the total number of operating time slots as requested in the household m, respectively.

3.3 Mathematical Formulation

In our previous work [4] the household DSM model aimed to minimize electricity costs by scheduling the on/off status of domestic appliances over the operational period considering dynamic electricity prices and locally available PV generation. The previous algorithm also considered a penalty factor which accounted for the inconvenience to the customer caused by the time shift in appliance operation.
In this work, the optimization model developed based on this system is expanded to include multiple feeders and scaled-up community size. The performance of the DSM will have tested in two suggested scenarios:

3.4 DSM with PV Peneterations

In this scenario we test the performance of the proposed DSM on the four households, with each assumed to have local rooftop PV. The results obtained

$$X_{CDSM}(t) = V(t), P_L(t), PLoss(t)_{CDSM} \quad (3.1)$$

The results obtained from ${P_L}^C DSM(t)$ will represent the optimal load profile of the household, and $P_Loss^C DSM$ represents the total power loss of the feeder.

$$\min C_e^m + C_p^m \quad (3.2)$$

Subject to:

$$\underset{e}{\overset{m}{C}} = 0.5 \times \sum_{t=1}^{T} P_{load}^m(t)\pi_e(t) \tag{3.3}$$

$$C_e^p = 0.5 \times \sum_{a,m}^{A} m\pi_p \cdot r_{a,m} \cdot \Delta T_{a,m=1} \tag{3.4}$$

$$p_{load}^{m}(t) = \max((\sum_{a,m=1}^{Am} r_{a,m} \times u_{a,m}(t) - \alpha \cdot p_{pv}^{m}(t)), 0) \tag{3.5}$$

$$\sum_{a,m=1}^{Am} r_{a,m} \times u_{a,m}(t) \leq MD^{m} \qquad \forall\, a \in \{1 \ to \ A_m\} \tag{3.6}$$

$$\sum_{t=1}^{T} u_{a,m}(t) = D_{a,m} \qquad \forall\, a \in \{1 \ to \ A_m\} \tag{3.7}$$

$$u_{a,m}(t) = 0 \qquad \forall\, t < S_{a,m} \quad or \quad \forall\, t > \ f_{a,m} \tag{3.8}$$

$$\Delta T_{a,m} = 1^{T} \cdot |t_{a,m}^{st_{new}} \ - t_{a,m}^{st_{old}}| \qquad \forall\, a \in \{1 \ to \ A_m\} \tag{3.9}$$

$$t_{a,m}^{st_{new}} = [t|u_{a,m}^{new}(t) = 1]_{1 \times D_{a,m}} \qquad \forall\, a \in \{1 \ to \ A_m\} \tag{3.10}$$

$$t_{a,m}^{st_{old}} = [t|u_{a,m}^{old}(t) = 1]_{1 \times D_{a,m}} \qquad \forall\, a \in \{1 \ to \ A_m\} \tag{3.11}$$

$$[v(t)] = f_{AC} \ (P_g(t), \ P_g^{PV}(t), \ P_L^{*}(t) \mid Y_{bus}) \tag{3.12}$$

$$E_{loss} = \sum_{t=1}^{T} \ \sum_{l=1}^{L} \mid i_L^t \mid^2 \ R_L \tag{3.13}$$

$$\sigma_v = \sqrt{\frac{1}{TN} \sum_{t=1}^{T} \sum_{i=1}^{N} (v_i^t - \overline{v})^2} \tag{3.14}$$

Where m is the home index, $u_{a,m}$ is the operation status of the appliance a; its 0 when the appliance is off, and 1 when it ON, with following format:

$[u_{a,m}(t)]_{A \times T} = [u_1^1, \, u_1^2, ..., \, u_1^T; \, u_1^1, \, u_2^2, ..., \, u_2^T; ....; \, u_A^1, \, u_A^2, ..., \, u_A^T]$

T refers to number of time slots, $T = 48$, and t is the time slots index. The household appliances were modeled using the measurable factors: s_a, f_a, r_a and D_a, where $[s_{a,m}, f_{a,m}]$ are parameters define the operating period when the household appliance a can be operated, $r_{a,m}$ and $D_{a,m}$ for the appliance power rating and the time duration of the appliance a respectively.

Where (3.2)and (3.3) for the electricity and for the penalty cost; Eq.(5) Eq. 3.5) to remove the negative cost. In this model, the surplus gene tarted power from PV can be delivered in to the grid with zero reward, therefore the cost at each time slots should be not less than zero α in Eq. (3.5) is a binary parameter stands for status of PV installation at DSM household. The Maximum load to use at each time slots was indicated in (3.6).This load limit can help in prevention of occurrence the load peak even when the electricity price is low.

Constraints (3.7) and (3.8) defines total operation time status of an appliance. Constraint (8)indicates the number of the tome slots shifted by calculate the difference between the old slots and the new slots. Constraints (3.9) and (3.10) specify the old time slot before shifting and the starting time slots, $t_{a,m}^{st_{old}}$ and $t_{a,m}^{st_{new}}$ respectively, to specify the time duration of the incorruptible appliances.

Constrain (3.12) for load flow calculation Where $P_g(t)$ injected power from substation is,$P_g^{PV}(t)$ is available PV generation, and $P_L^*(t)$ is the electrical load after DSM scheduling. (3.13) Calculates the system power loss where i_L^t is current of the feeder L at time t and R_L is resistance of line L. (3.14) defines the voltage fluctuation (σ_v) index with v_i^t as the voltage of bus i at time t and $\overline{v} = \sum_{t=1}^{T}\sum_{i=1}^{N} v_i^t$ as average voltage in the network.

Normally when there is no shift the penalty cost is zero ($C_p = 0\,\$/\text{day}$) which means there is no time shifting slots for the operated appliances and ($\Delta T_a = t_{a,m}^{st_{new}} - t_{a,m}^{st_{old}} = 0$), in this case consume has to pay for the consumed energy kW/h as electricity C_e based on the TOUP. With optimal shifting the total cost that consumer has to pay will reduced due to the cost saving (C_{saving}) in c/kWh that comes after shift the operation time from high price to low price period, in this case consumer will pay extra cost as penalty cost. Its important to mention that the algorithm make shift whenever there is cost saving in another world ($C_{saving} > C_p$) and the total cost paid by consumer is ($C_e - C_{saving} + C_p$).

3.5 DSM without PV Penetrations

In this scenario, the method is tested on each of the four houses, assuming that PV is rooftop-connected to households that are on the same feeder line but do not participate in DSM. The results obtained $\mathrm{X}^d DSM(t) = V(t), P_L(t)$,$P_L oss(t) dDSM$. In this case, power generated by PV is considered zero in the calculation of electricity cost C_e^m. The results obtained from ${P_L}^d DSM(t)$ again represent the optimal load profile of the household, and $P_L oss^d DSM$ denotes the total power loss of the feeder.

$$\min C_e^m + C_p^m \qquad (3.15)$$

Subject to:

$$\underset{e}{\overset{m}{C}} = 0.5 \times \sum_{t=1}^{T} P_{load}^m(t)\pi_e(t) \tag{3.16}$$

$$C_e^p = 0.5 \times \sum_{a,m=1}^{A} m\pi_p \cdot r_{a,m} \cdot \Delta T_{a,m} \tag{3.17}$$

$$p_{load}^m(t) = (\sum_{a,m=1}^{Am} r_{a,m} \times u_{a,m}(t)) \tag{3.18}$$

$$\sum_{a,m=1}^{Am} r_{a,m} \times u_{a,m}(t) \leq MD^m \qquad \forall\ a \in \{1\ to\ A_m\} \tag{3.19}$$

$$\sum_{t=1}^{T} u_{a,m}(t) = D_{a,m} \qquad \forall\ a \in \{1\ to\ A_m\} \tag{3.20}$$

$$u_{a,m}(t) = 0 \qquad \forall\ t < S_{a,m} \quad or \quad \forall\ t >\ f_{a,m} \tag{3.21}$$

$$\Delta T_{a,m} = 1^T \cdot |t_{a,m}^{st_{new}} - t_{a,m}^{st_{old}}| \qquad \forall\ a \in \{1\ to\ A_m\} \tag{3.22}$$

$$t_{a,m}^{st_{new}} = [t|u_{a,m}^{new}(t) = 1]_{1 \times D_{a,m}} \qquad \forall\ a \in \{1\ to\ A_m\} \tag{3.23}$$

$$t_{a,m}^{st_{old}} = [t|u_{a,m}^{old}(t) = 1]_{1 \times D_{a,m}} \qquad \forall\ a \in \{1\ to\ A_m\} \tag{3.24}$$

$$[v(t)] = f_{AC}\ (P_g(t),\ P_g^{PV}(t),\ P_L^{*}(t)\ |\ Y_{bus}) \tag{3.25}$$

3.6 Numerical Simulations and Results

This section applies the proposed household DSM approach over the two scenarios. For this scenario, the voltage load profile $\mathrm{V}^0(t), the original load profile \mathrm{P}_L^o(t)$, and the active power loss $P_Loss^o(t)$ must be calculated for each of the four households. The obtained results $\mathrm{X}^O(t) = V^0(t), P_L^o(t), P_Loss^o(t)$ from the AC power flow equation will be compared with the results from the DSM algorithm. Fig. 19 shows the original households consumption profiles of the smart homes without DSM scheduling with maximum peak as specified in Table 1. Each of the four profiles in Table 1 represents customer preference, which indicates two demand peaks from 7:00 to 9:00 and from 17:00 to 20:00. As depicted in the price signal Fig.2A) there is a peak price rate during the peak load, such that the peak demand from 17:00 to 20:00 will cost much more than any other time

3.6.1 DSM with PV

Fig.19 Illustrates the original load profiles for each household. The performance of the implemented DSM algorithm was tested on two configurations. In the first scenario, the four households are connected in locations 12, 14, 17, and 22 of the line feeder, and each household has rooftop PV. The result is a significant improvement in the daily load consumption pattern and a reduction of total electricity cost. According to Fig 20. The cost of households 1, 2, 3, and 4 were \$4.08, \$6.41, \$3.88, and \$3.65 per day, respectively.

Comparing those costs with the original costs in Fig. 19, household 1 sees a reduction of 76%. In households 2, 3, and 4, the cost reduction is 70%, 70.23%,

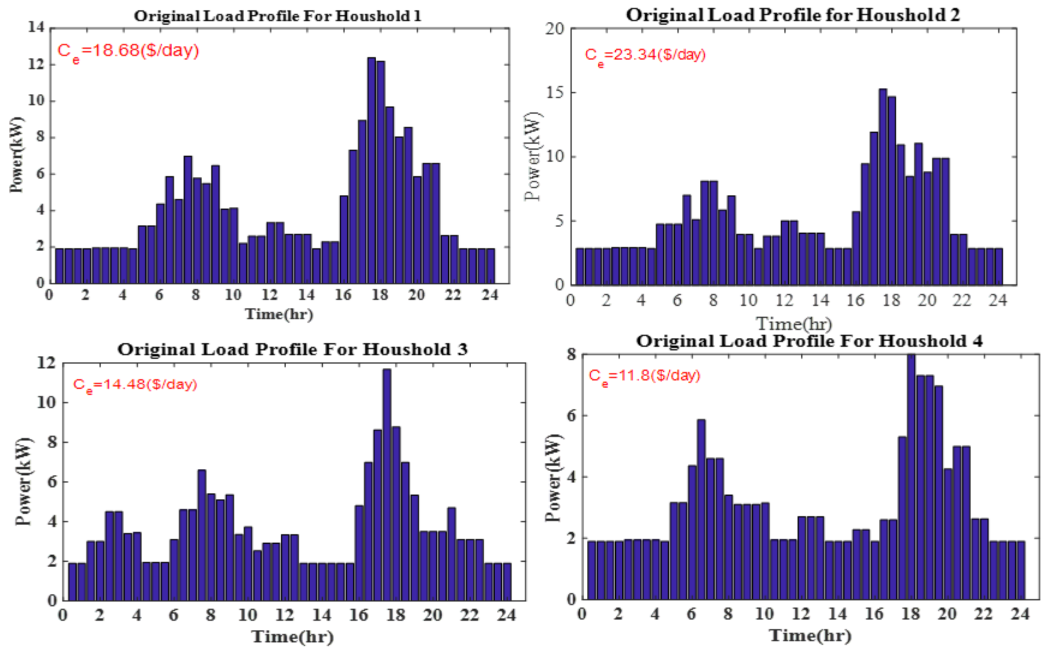

Fig. 19. Original households consumption profile with DSM

and 66%, respectively. Most peak loads during high-priced hours moved to off-peak periods, except for the non-flexible appliances. Also, with local PV generation, during the time slots with PV availability, appliance operation is free.

Fig. 21 shows the impact of applying different penalty pricing on load shifting. As we can see, at $\pi_p = 5$ c/kWh, the final consumption profile is considerably different from Fig. 20. In fact, as the penalty cost becomes larger, the final consumption profile increasingly resembles the original profile because the penalties prevent the profitable time-shifting of loads. Indeed, at $\pi_p = 20$ c/kWh, despite surplus PV generation between 10:00 and 14:30, the final load profile closely resembles the original load profile. When the DSM algorithm is applied to a system with available PV generation, more appliances shift to the time slots between 14:00 and 16:00, compared to the case without PV generation (contrast Fig. 20 with Fig. 22).

Table 3.2 summarizes the impact on PV utilization of applying the proposed

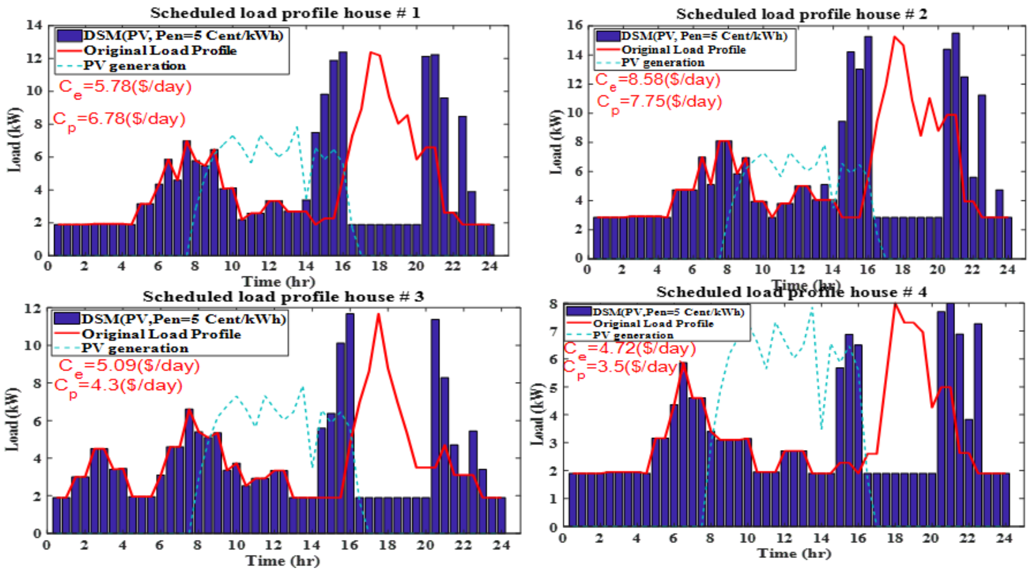

Fig. 20. Consumption profile for each household with DSM (PV, $\pi_p = 0$ c/kWh)

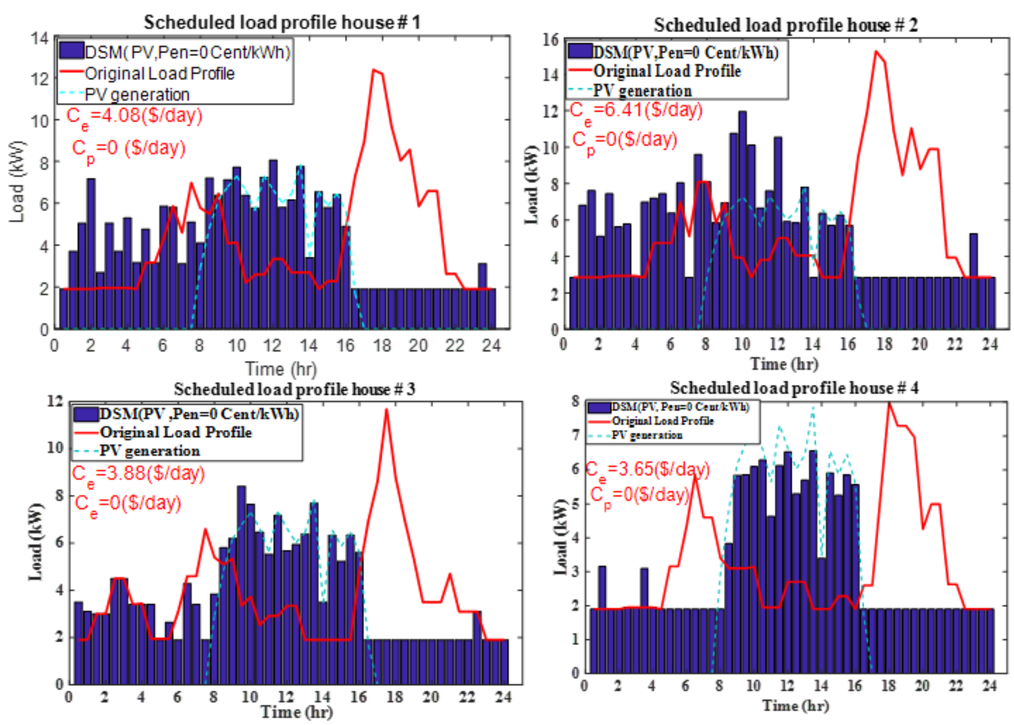

Fig. 21. Consumption profile for each houshold with DSM $\pi_p = 0$ c/kWh)

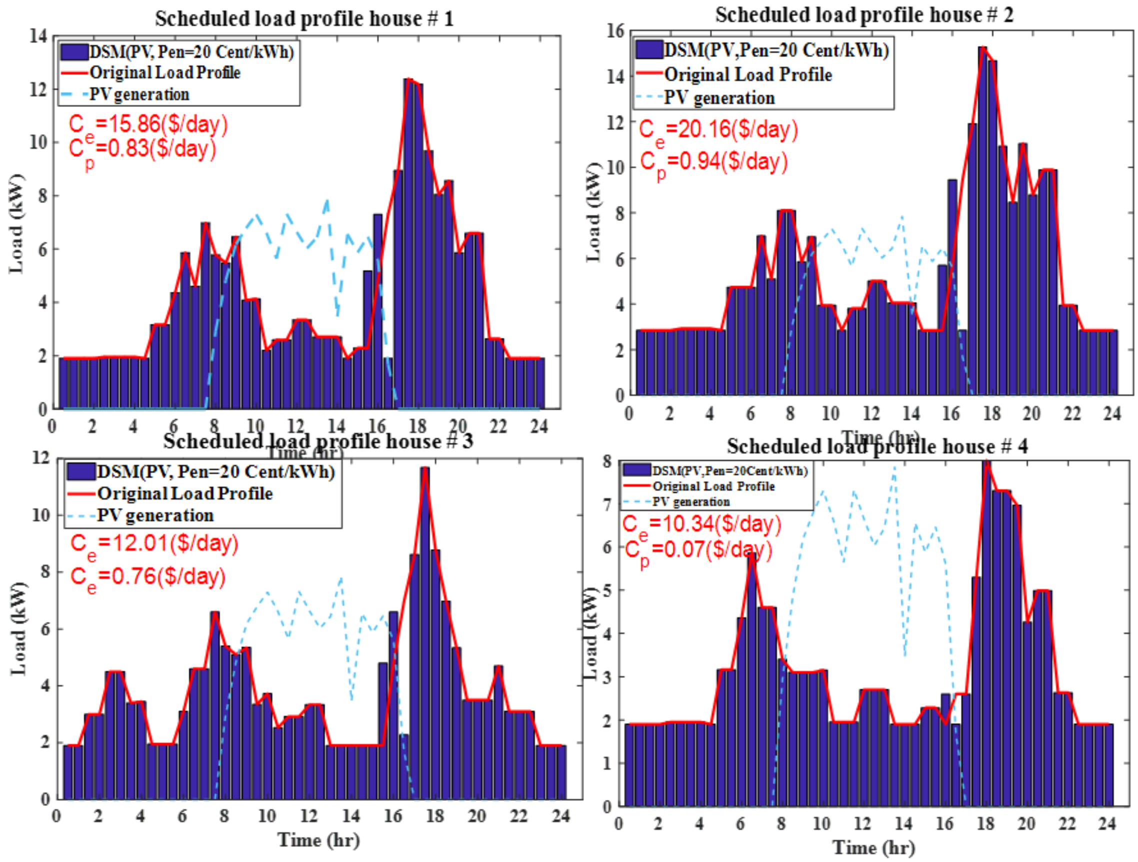

Fig. 22. Consumption profile for each houshold with DSM $\pi_p = 20$ c/kWh)

Table 3.2: PV utilization efficiency at different penalty price π_p = [¢/kWh]

	PV Utilization Efficiency			
Penalty Price π_p = [¢/kWh]	Household 1	Household 2	Household 3	Household 4
0	98%	97.6%	97.4%	88%
5	68.3%	77.84%	63.48%	52.24%
10	62.5%	73.11%	58.1%	45.64%
20	58.4%	69.64%	54.5%	42.09%

DSM algorithm at various penalty factors π_p; specifically, that as penalty pricing increases, PV utilization efficiency suffers. Thus, the opportunity to use free and clean PV-generated power at highest utilization efficiencies (occurring at $\pi_p = 0$ c/kWh is lost.

3.6.2 DSM without PV Different Site [dDSM]

In the second scenario, the four households participate in the proposed DSM program without local PV power generation. The four homes are found at locations 8, 15, 22, and 25 of the feeder, while the four rooftop PVs are installed in different sites along the same feeder. The performance of the proposed DSM algorithm can be seen in Fig. 23. The red solid line represents original load profile. With an optimal appliance operation schedule, a new set of shifted consumption profile will be achieved with the total daily cost reduced to \$5.91, \$8.47, \$5.70, and \$5.37 for households 1, 2, 3, and 4, respectively. This corresponds to 68.36%, 63.7%, 60.63%, and 54.4% savings, respectively. Fig. 23 also indicates that most demand, apart from non-flexible appliances, has been moved from high-priced hours to off-peak periods.

Table 3.3 contains a summary of the obtained results for both scenarios. As in the previous section, the penalty pricing factor influences the customers willingness to participate in the DSM program. With increasing penalty factor, household electricity costs approach the original household costs before DSM.

A comparison of power losses at various penalty prices is tabulated in Table 3.4. Again, we see that the customers power and cost-saving opportunities become increasingly limited as penalty prices rise. They cannot profitably leverage PV generation or demand time-shifting. In particular, the time-shifting of uninterruptible loads, since they must operate continuously once started, becomes infeasible at the highest penalties.

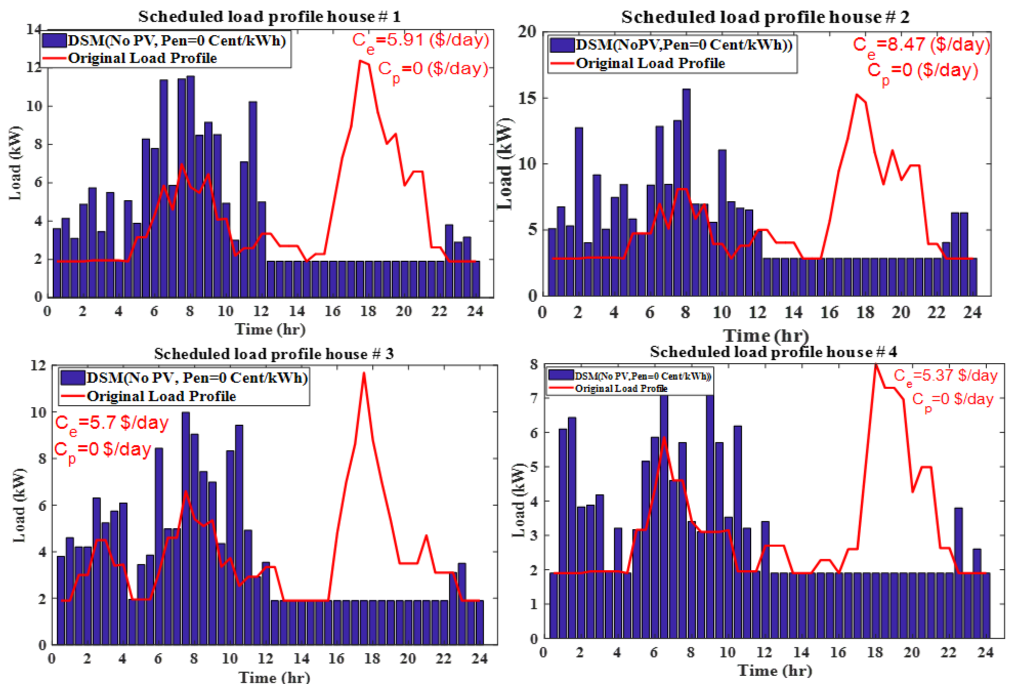

Fig. 23. Consumption profile for each houshold with DSM (No PV, $\pi_p = 0$ c/kWh)

$$[v(t)] = f_{AC}\ (P_g(t),\ P_g^{PV}(t),\ P_L^*(t)\ |\ Y_{bus}) \tag{3.26}$$

The power flow equation (Eqn. 13) is applied to evaluate the voltage profile at each household bus connected to the line feeder in the two cases. As depicted in Fig. 24, the voltage along the feeder always stays within specification (i.e., between 0.95 and 1.05 P.U.), including in locations 12, 14, 17, and 22 which are managed by the proposed DSM.

3.7 Conclusion

With this chapter, a developed DSM algorithm which can be scaled to large communities of residential households with differing capacities, based on the day-ahead price signal and the availability of local PV generation. On top of improving PV

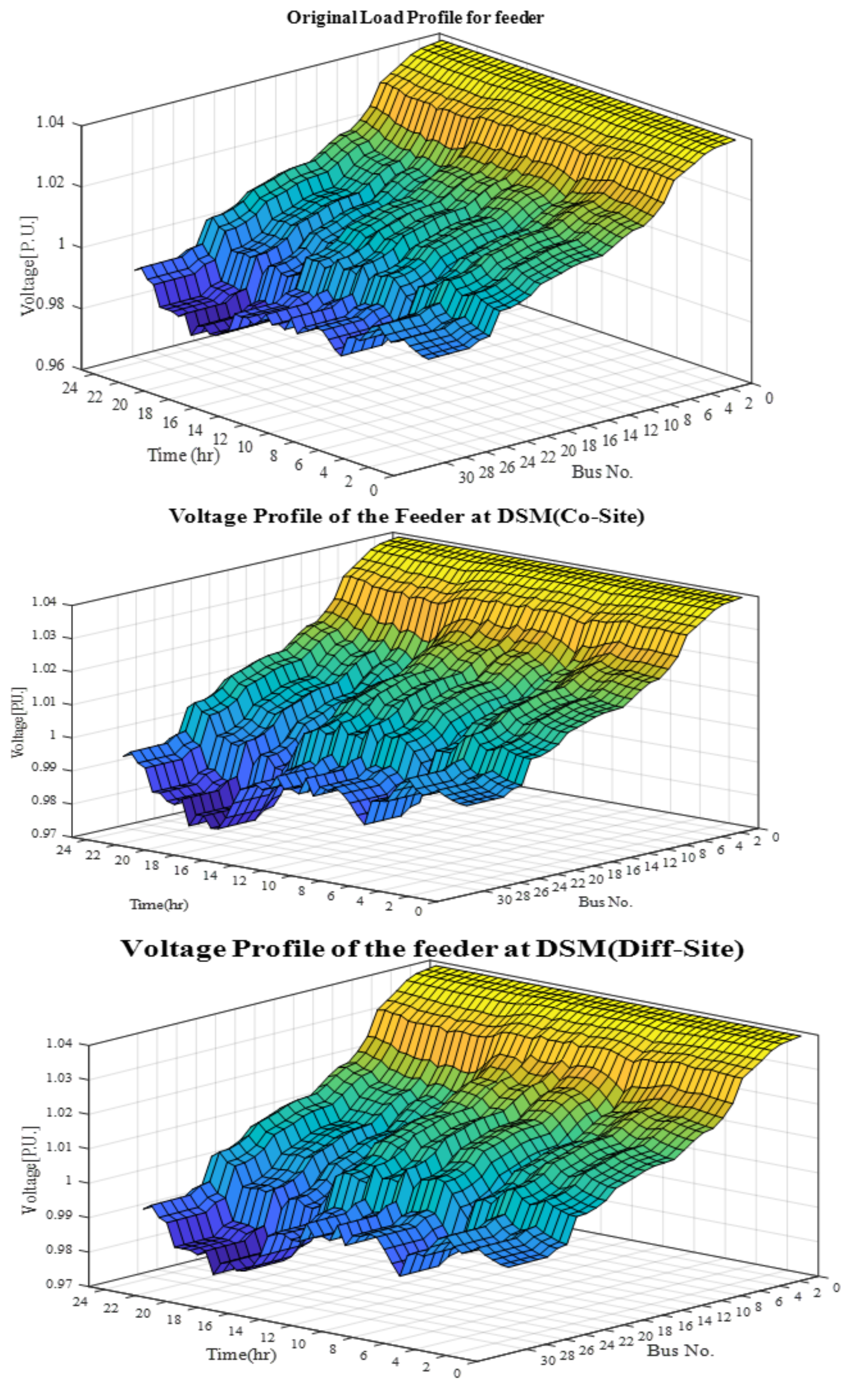

Fig. 24. Voltage profile of the feeder

Table 3.3: Comparison of costs for the two Scenario

(Diff − Site) $\pi_p = 0, 5, 10$ [¢/kWh]							(Co − Site) $\pi_p = 0, 5, 20$ [¢/kWh]					
H	C_e [$/day]			C_p [$/day]			C_e [$/day]			C_p [$/day]		
1	**5.9**	**7.9**	**14.5**	**0**	**6.6**	**2.7**	**4.0**	**5.8**	**11.9**	**0**	**6.7**	**3.5**
2	**8.4**	**10.9**	**18**	**0**	**7.5**	**3.85**	**6.4**	**8.5**	**15.7**	**0**	**7.7**	**4**
3	**5.7**	**7.1**	**11.1**	**0**	**4.1**	**2.4**	**3.8**	**5.0**	**8.7**	**0**	**4.3**	**3.7**
4	**5.3**	**6.4**	**9.9**	**0**	**3.3**	**1.3**	**3.6**	**4.7**	**8.4**	**0**	**3.5**	**1.4**

Table 3.4: Power loss calculation at different Penalties

	π_p=[¢/kWh]	Power Loss (kW)
Same Site with the household (Co-site)	0	164.22
	5	166.16
	10	167.24
	20	167.88
Different Site (Diff-Site)	0	165.5
	5	167.4
	10	168.59
	20	170.37

utilization and cost savings, voltage fluctuations are reduced, resulting in a smoother feeder voltage profile. We have shown the stifling effects of penalty pricing on PV utilization under this system, as illustrated by Table 2; increasing penalty price discourages households from shifting appliance use to off-peak hours, resulting in increased power losses. Our results in Table 3 demonstrate the potential to maximize cost savings via optimal usage of PV-generated power. Lastly, from the data in Table 4, we conclude that active participants in DSM programs can help reduce total power losses of the feeder. Our proposed DSM approach can help homeowners automatically create optimal load operation schedules based on comfort settings while considering dynamic electricity pricing and PV systems.

CHAPTER 4

OPTIMIZED ENERGY UTILIZATION IN SMALL AND LARGE COMMERCIAL LOADS AND RESIDENTIAL AREAS

4.1 Introduction

In smart grid, the demand side management (DSM) techniques need to be designed to process a large number of controllable loads of several types. In this chapter, we proposed a framework to study the demand side management in smart grid which contains a variety of loads in two service areas, one with multiple residential households, and one bus with commercial customers.

Specifically, each household may have renewable generation as well as interruptible and uninterruptible appliances to make individual scheduling to optimize the electric energy cost by making the best time of the electricity usage according to the day ahead forecast of electricity prices. A high load bus represents a commercial area employed to demonstrate the impact of high load at any bus on voltage profile, power loss, and load flow condition, and to show the performance of the proposed DSM for large number of appliance. Using the developed simulation model, we examine the performance of the proposed DSM and study their impact on the distribution network operation and renewable generation, overall voltage deviation, real power loss, and possible problems such as reverse power flows, voltage rise have examined and compared, these problems can easily be seen at the commercial load bus. The benefits of DSM include financial and system reliability, among others. Financial benefits are gained in the bill savings and incentive payments earned by customers that adjust their electricity demand in response to time-varying electricity rates or

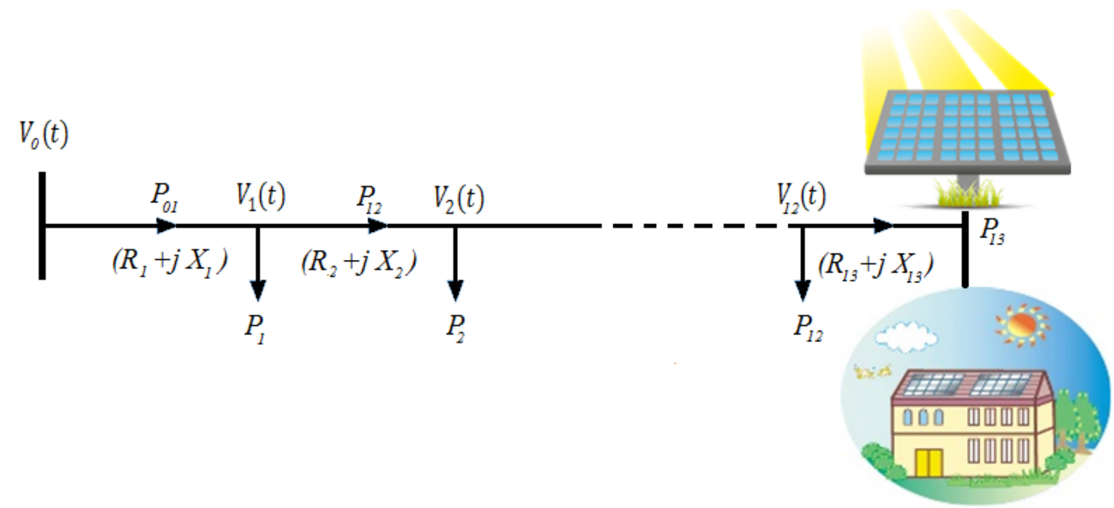

Fig. 25. Distribution network of households

incentive-based programs [1]. Reliability benefits are the operational security and adequacy savings that result because DSM lowers the likelihood and consequences of forced outages that impose financial costs and inconvenience on customers [2].

In the United States, many DSM programs are widely implemented by commercial and industrial customers. These are mainly interruptible load, direct load control, real-time pricing and time-of-use programs [3]. On the other hand, very few DSM programs are in use today for residential customers. Authors in [4] put forward a scheduling approach of operation and energy consumption of various electrical appliances in a grid connected smart home system.

Reference [5] and [6] introduced an algorithm that simulated residential load shifting under time of use (TOU) regimes using previously generated profile data to model realistic demand response behavior. Reference [7] shows the economic benefits of DSM on the agriculture and industrial sectors. Majority of DSM application have focused on large commercial loads, these loads have a large amount of demand to make a considerable contribution to the stability of the grid [8].

In this chapter develops an optimization model for a multiple residential households and two size of commercial loads with a rooftop PV installation. This algorithm has the ability to take into consideration the evolution of the system performance in terms of operation parameter such as voltage fluctuation, power loss of the entire system, and the PV utilization efficiency while optimizing the electricity cost. In addition the proposed algorithm can handle large number of controllable appliances in two types of loads residential and commercial taking into consideration the fact that certain appliances may have higher priority over other appliances so that these appliances may shifted to the suitable time according to their importance.in the simulation process the algorithm classifies the commercial appliances into three categories: high, med and low. The appliances in each category subjected to different penalty prices according to the importance of the appliance.

4.2 System Modeling

This section describes a system model for the proposed DSM in a single radial distribution network with thirty buses to demonstrate the effectiveness of the proposed approach, the DSM strategy is tested on two different areas, each with different type of customers; residential and commercial. Each area has different type of controllable appliances.

4.2.1 Residential Community Area

As depicted in Fig. 25, bus 1 represents a substation while the rest of the buses represent the simulated residential community with up to 29 households with a more diverse combination of appliances. Each smart home will optimize individually using the proposed decentralized DSM algorithm its appliance operation schedule to save electricity costs according to the day-ahead residential and commercial time of use

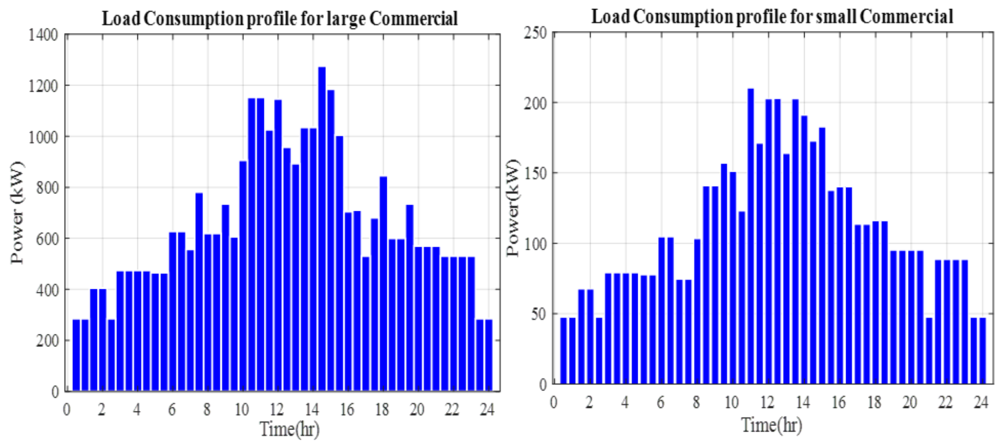

Fig. 26. Large Commercial and small Load

pricing (TOU) as shown in Fig. 27 and rooftop PV (if available).

4.2.2 Commercial Area

The devices subjected to load control in the commercial area (delivered by Bus No.17) have consumption ratings which are slightly higher than those in the. Fig.26 show the curves for the one commercial activity, also the curve show that there is one peak load occurs during the period from 9:00 AM to 5:00 PM. Each appliance is modeled using four parameters s_a, f_a,r$_a$ and D$_a$, $where$s$_a$, f_a defines the allowable operating time during which the appliance a may be switched on, r_a and D_a denote the power rating and the total number of operating time slots as requested, respectively.

4.3 Mathematical Formulation

The DSM optimization for each household can be defined as below:

$$\min C_e^m + C_p^m \qquad (4.1)$$

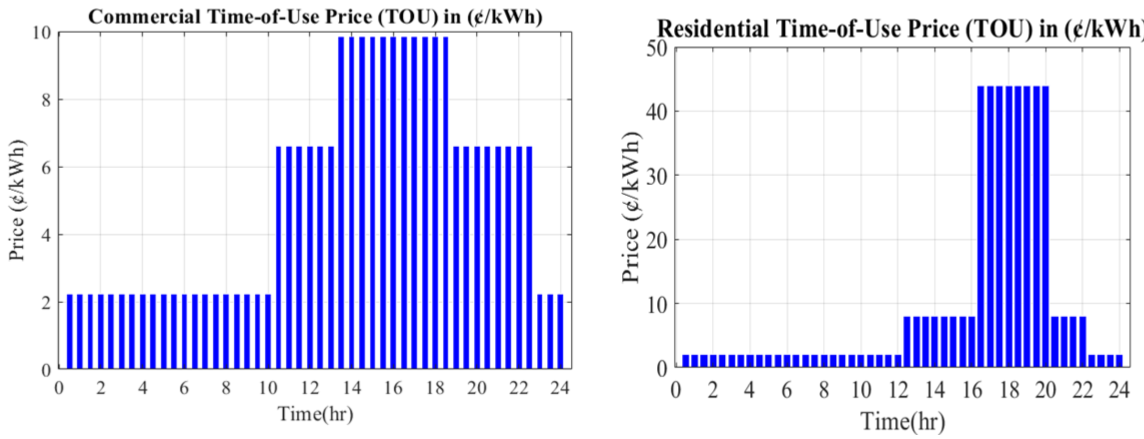

Fig. 27. Time-of Use (TOU) Price for Residential and Commercial loads

Subject to:

$$\overset{m}{\underset{e}{C}} = 0.5 \times \sum_{t=1}^{T} P_{load}^{m}(t)\pi_e(t) \tag{4.2}$$

$$C_e^p = 0.5 \times \sum_{a,m=1}^{Am} \pi_p \cdot r_{a,m} \cdot \Delta T_{a,m} \tag{4.3}$$

$$p_{load}^{m}(t) = (\sum_{a,m=1}^{Am} r_{a,m} \times u_{a,m}(t)) \tag{4.4}$$

$$\sum_{a,m=1}^{Am} r_{a,m} \times u_{a,m}(t) \leq MD^m \qquad \forall\ a \in \{1\ to\ A_m\} \tag{4.5}$$

$$\sum_{t=1}^{T} u_{a,m}(t) = D_{a,m} \qquad \forall\ a \in \{1\ to\ A_m\} \tag{4.6}$$

$$u_{a,m}(t) = 0 \qquad \forall\ t < S_{a,m} \quad or \quad \forall\ t > f_{a,m} \tag{4.7}$$

$$\Delta T_{a,m} = 1^T \cdot |t_{a,m}^{st_{new}} - t_{a,m}^{st_{old}}| \qquad \forall\ a \in \{1\ to\ A_m\} \tag{4.8}$$

$$t_{a,m}^{st_{new}} = [t|u_{a,m}^{new}(t) = 1]_{1 \times D_{a,m}} \qquad \forall\ a \in \{1\ to\ A_m\} \tag{4.9}$$

$$t_{a,m}^{st_{old}} = [t|u_{a,m}^{old}(t) = 1]_{1 \times D_{a,m}} \qquad \forall\ a \in \{1\ to\ A_m\} \tag{4.10}$$

$$[v(t)] = f_{AC}\ (P_g(t),\ P_g^{PV}(t),\ P_L^*(t)\ |\ Y_{bus}) \tag{4.11}$$

T refers to number of time slots, $T = 48$, and t is the time slots index. The household appliances were modeled using the measurable factors: s_a, f_a, r_a and D_a, where $[s_{a,m}, f_{a,m}]$ are parameters define the operating period when the household appliance a can be operated, $r_{a,m}$ and $D_{a,m}$ for the appliance power rating and the time duration of the appliance a respectively. Where (2)and (3) for the electricity and for the penalty cost; Eq.(4) Eq. (4) to remove the negative cost.

In this model, the surplus gene tarted power from PV can be delivered in to the grid with zero reward, therefore the cost at each time slots should be not less than zero α in Eq. (4) is a binary parameter stands for status of PV installation at DSM household. The Maximum load to use at each time slots was indicated in (5).This load limit can help in prevention of occurrence the load peak even when the electricity price is low.

Constraints (6) and (7) defines total operation time status of an appliance. Constraint (8)indicates the number of the tome slots shifted by calculate the difference between the old slots and the new slots. Constraints (9) and (10) specify the old time slot before shifting and the starting time slots, $t_{a,m}^{st_{old}}$ and $t_{a,m}^{st_{new}}$ respectively, to specify the time duration of the incorruptible appliances.

constrain (11) for load flow calculation Where $P_g(t)$ injected power from substation is,$P_g^{PV}(t)$ is available PV generation, and $P_L^*(t)$ is the electrical load after DSM scheduling. (12) Calculates the system power loss where i_L^t is current of the feeder L at time t and R_L is resistance of line L. (13) defines the voltage fluctuation (σ_v) index with v_i^t as the voltage of bus i at time t and $\overline{v} = \sum_{t=1}^{T} \sum_{i=1}^{N} v_i^t$ as average voltage in the network.

4.4 Numerical Simulation Results

4.4.1 DSM Residential Area

The red sold line illustrates the original load profiles for each household. The performance of the implemented DSM algorithm was tested on two configurations. Each of the 29 households has rooftop PV. The result is a significant improvement in the daily load consumption pattern and a reduction of total electricity cost. According to Fig. 28. The cost of households 1, 2, 3, and 4 were 4.08,6.41, $3.88, and 3.65$ per day, respectively. Comparing those costs with the original costs, household 1 sees a reduction of 76%. In households 2, 3, and 4, the cost reduction is 70%, 70.23%, and 66%, respectively. Most peak loads during high-priced hours moved to off-peak periods, except for the non-flexible appliances. Also, with local PV generation, during the time slots with PV availability, appliance operation is free.

4.5 Voltage Fluctuations

To check if there is any voltage violation, Fig. 29 clarify the voltage deviation of the Bus No. 17 for the small commercial load, as we can see that there was a slight difference between the voltage profile in case of considering DSM with PV, the voltage increased between the 12:30 pm and 4:00 pm as most of the demanded load covered by the generated PV power. In other word, the voltage rise due to the reverse power flow can be suppressed by reducing the amount of active power produced by PV. In this work, Voltage rise occurs when the load demand is low and the PV generation in its max level. The possible solution for voltage rise can be done during our simulation by either reduce the network resistance. Or by reduce the PV penetration Level. As we can see the reduction in the PV penetration level to the half caused slight reduction in voltage level. Maximum and minimum feeder voltages

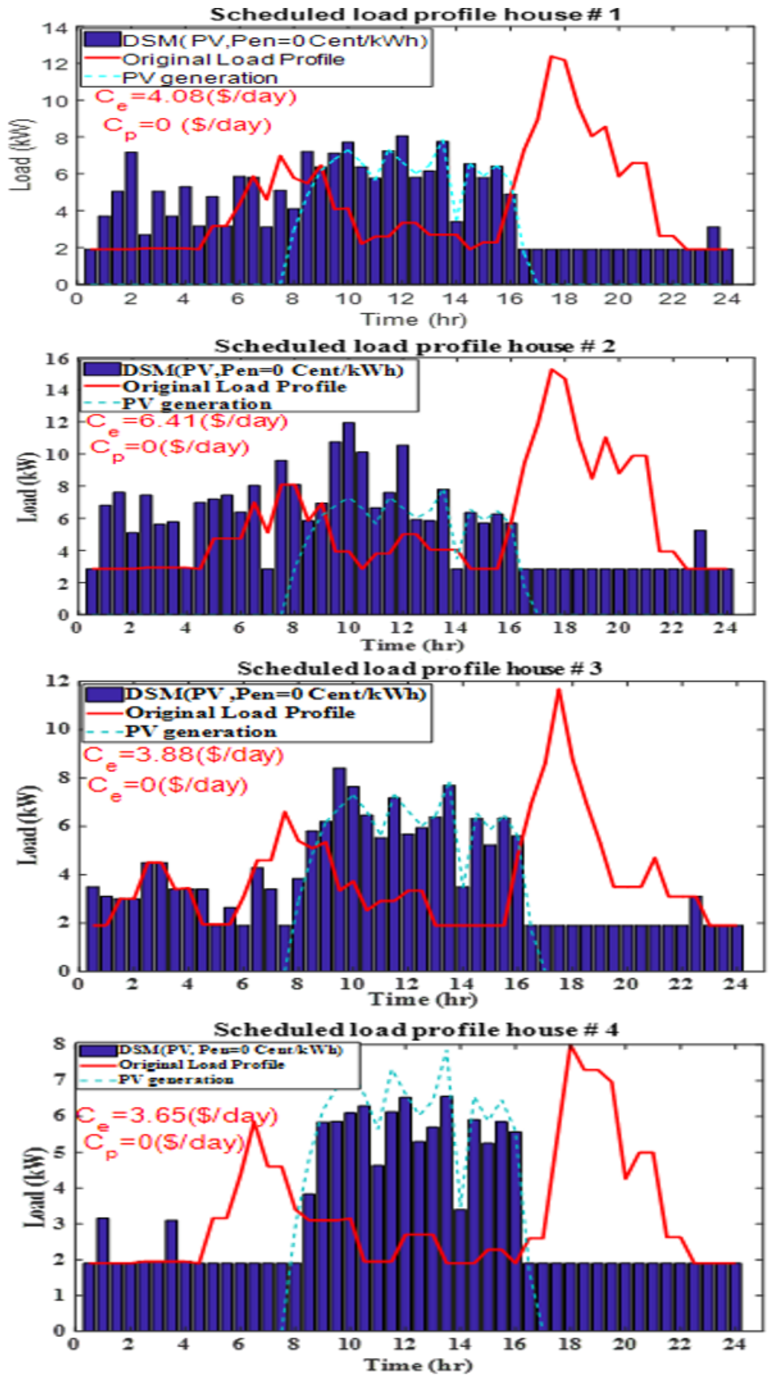

Fig. 28. DSM four different conditions

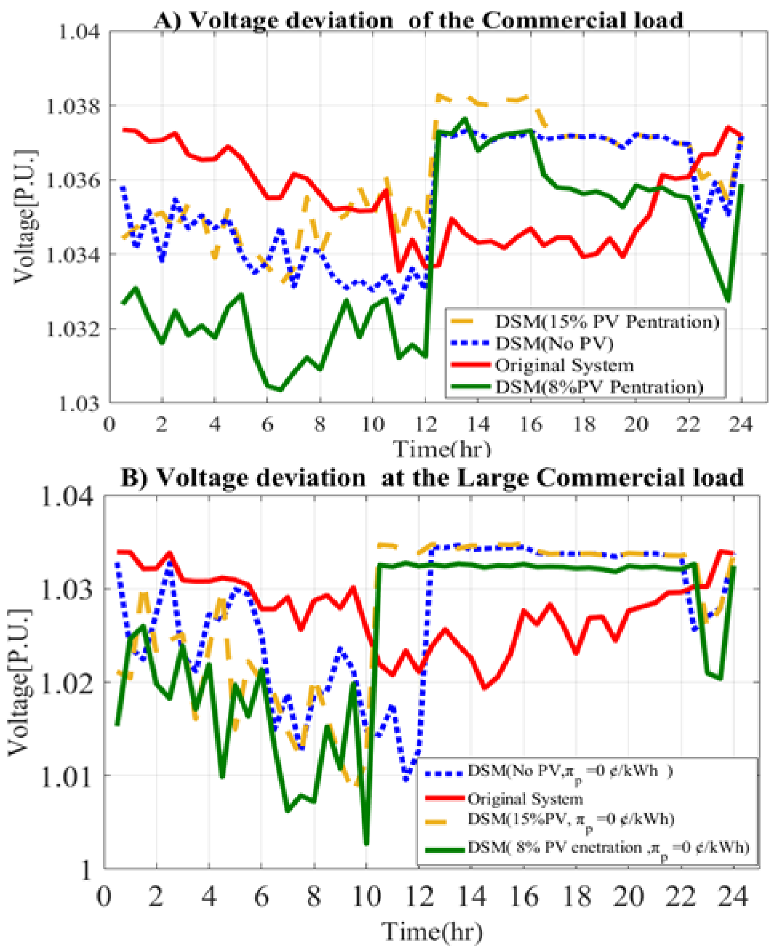

Fig. 29. Voltage profile at commercial load

were recorded for each simulation, and simulations were continued at increasing PV levels as depicted in Fig. 29.

4.6 Real Power loss

From Fig. 30, it is clearly that, the power loss decrease when injecting PV generated power. As we can see during the time 8 : 00 am - 12 : 30 pm the power loss reduced. The overall reduction in power loss was 26%. As in Fig. 15 (A) black dotted line, the case of DSM (No PV, $\pi_p = 0$ c/kWh) there is an increased in the power loss between 8 Am and 12:00 PM, the load demand at this time is high ,also the current drawn from the grid will be high .The blue dotted line is the feeder power loss in the presence of solar PV generation, as in Fig. 30 in the time from 8:00 AM to 12:00 the power loss has significant reduction, this is because both of the loads are consumed the power from the solar PV, and consequently, the current reduced.

Table II summarized the effectiveness of considering high tariff on the efficiency of the solar PV usage, it shows that the efficiency of the solar PV usage dropped for the residential area, while it in-creased in the commercial building as PV highest power generated at the period of peak commercial load [see Fig. 26].Generally, the feeder power losses calculation done using the formula:

$$P_{loss} = \sum_{i=1}^{n_{br}} |I_i|^2 r_i \tag{4.12}$$

Where n_{br} : number of nodes in the feeder, $|I_i|$: is the node current, r_i is the resistance.

4.6.1 DSM in the Commercial Area

Fig.31 shows that when assuming $\pi_p = 0$ c/kWh more load moved to time slots with low price periods.as stated in the introduction for a more realistic scenario, the proposed algorithm also take into consideration the fact that certain appliances may have higher priority over other appliances so that these appliances have to operate in their specified time; hence these types of appliances have less DSM participation.

The obtained results for the commercial area are given in Figs (32 a-b), and 33,

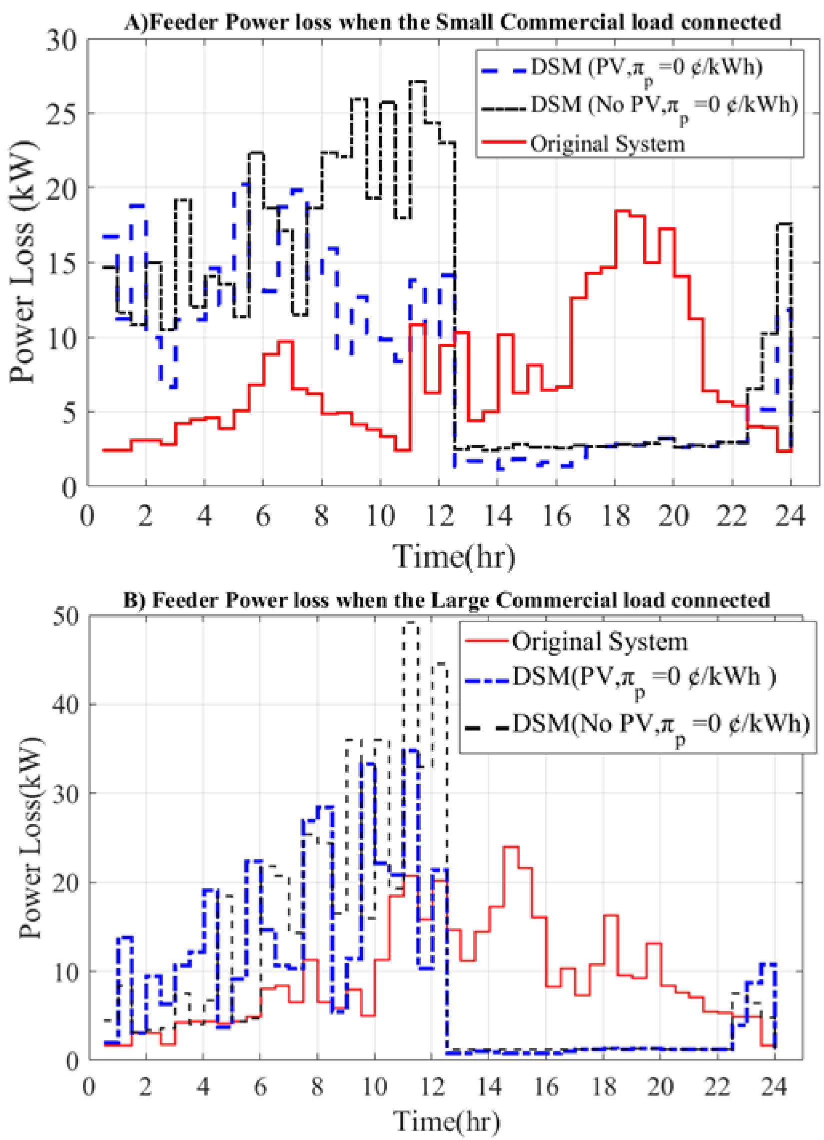

Fig. 30. Overall feeder power Loss when A) Small commercial load connected B) Large commercial load connected

Table 4.1: PV utilization efficiency at different penalty price $\pi_p = 0[¢/\text{kWh}]$

	PV Utilization Efficiency		
Penalty Price $\pi_p =$ [¢/kWh]	Residential Area	Penalty Price $\pi_p =$ [¢/kWh]	Commercial Area
0	98%	0	96%
5	68.3%	2	100%
10	62.5%	3	100%
20	58.4%	5	100%

the comparison of the preferred load [original load consumption] as it appears in sold line with the new profile after apply the DSM as in Figs 8 and 9 [green dotted line], also Figs 32 and 33 clarify that there is only a high load period from 9: 30 to 4: 30. Fig.34-a illustrates the cost saving of the shifted appliances and the corresponding penalty cost for $\pi_p = 0$, 1, 3 c/kWh which re-ported the penalty prices applied for Low, Med, and high critical respectively.

The obtained results show that one high critical appliance participated in the DSM with onetime slots shifts, while five appliances under Med-critical categories participated and shifted slots of the appliances increased, it is worth noting that the corresponding cost saving depends not only on reduced electricity price caused by the shifted slots but also on power rate of the appliance. Lastly for Low-critical we see that number of the appliances participating in DSM increase to nine with much higher cost saving and higher time shifted slots, also we see from Fig.34-(a) that the low-critical appliances have zero penalty cost as $\pi_p = 0$ c/kWh.

Fig. 37 clarify the voltage deviation of the original system, as we see that the voltage profile has decreased between the 10:00 AM and 5:00 pm as the load demand in highest level, in case of residential (at DSM $\pi_p = 0$ c/kWh), we see that the voltage profile starts to increase at 12:00 pm to 16:00 pm as the residential load shift to the

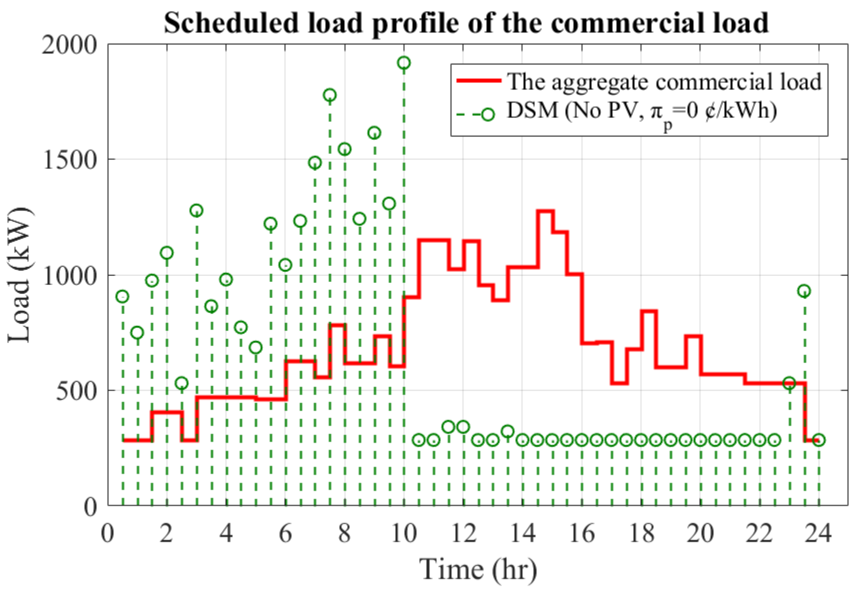

Fig. 31. DSM results for the commercial at $\pi_p = 0$ c/kWh

low price time from early morning to 11:30 am [see residential price Fig.5],beside, the availability of the PV power and reached the highest level at 1:30 pm and the overall the voltage profile in case of residential DSM more fluctuated and reached to 1.038 P.U. in some parts in compare to the original profile.

In case of commercial DSM, the voltage profile decreases during the early hours during the day when parts of the load rescheduled to the low-price time [see commercial price Fig.27] and increase during the daytime hours (8:00-16:00) when the rooftop PVs generate power, However, the DSM scheduling shift some appliance usage into those time slots and mitigate to any voltage violation may occurs.

4.7 DSM for Thirty Households and for Different Participation Level

Fig. 38 compares the voltage profile at the end of the feeder for different participation levels with $\pi_p = 0$ c/kWh considering the two scenarios, i.e., with PV

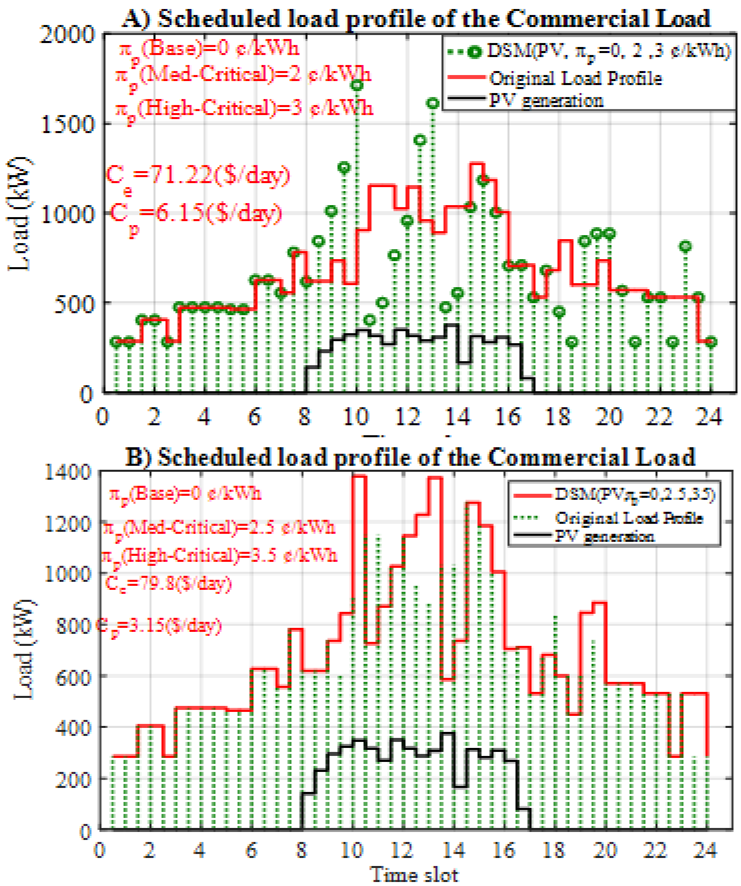

Fig. 32. A and B Represent DSM Results for commercial at Different π_p

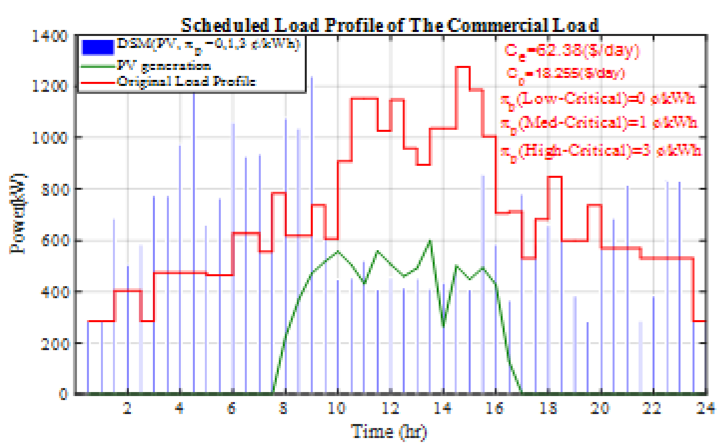

Fig. 33. Demand side management (DSM) of commercial Load

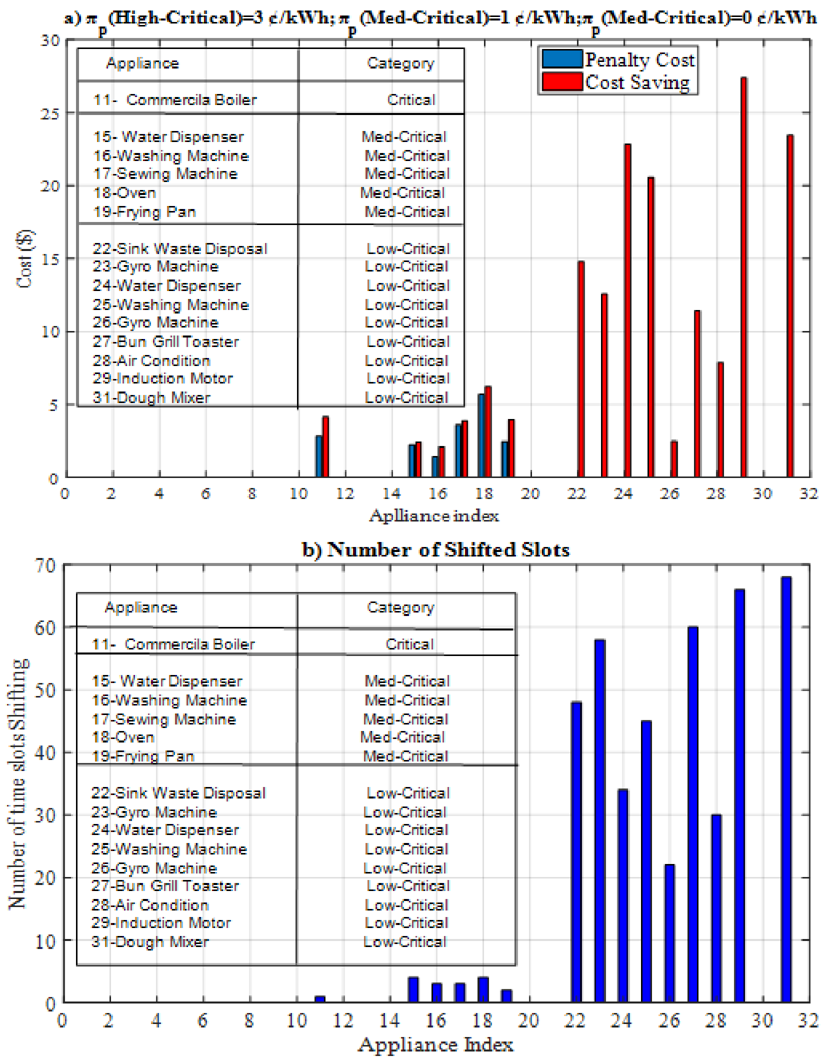

Fig. 34. Demand side management (DSM) of commercial Load

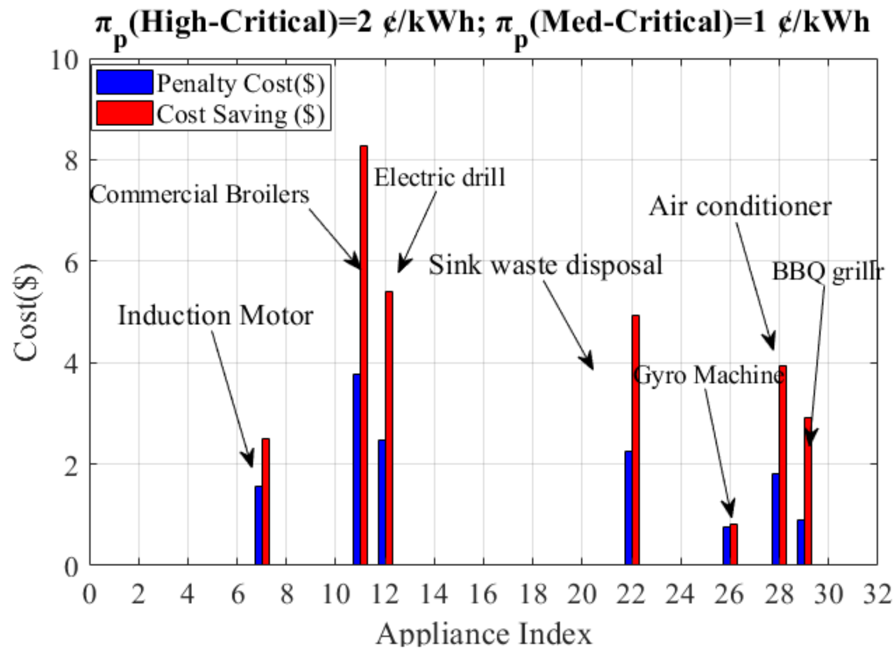

Fig. 35. Cost saving and Penalty Cost for Commercial DSM

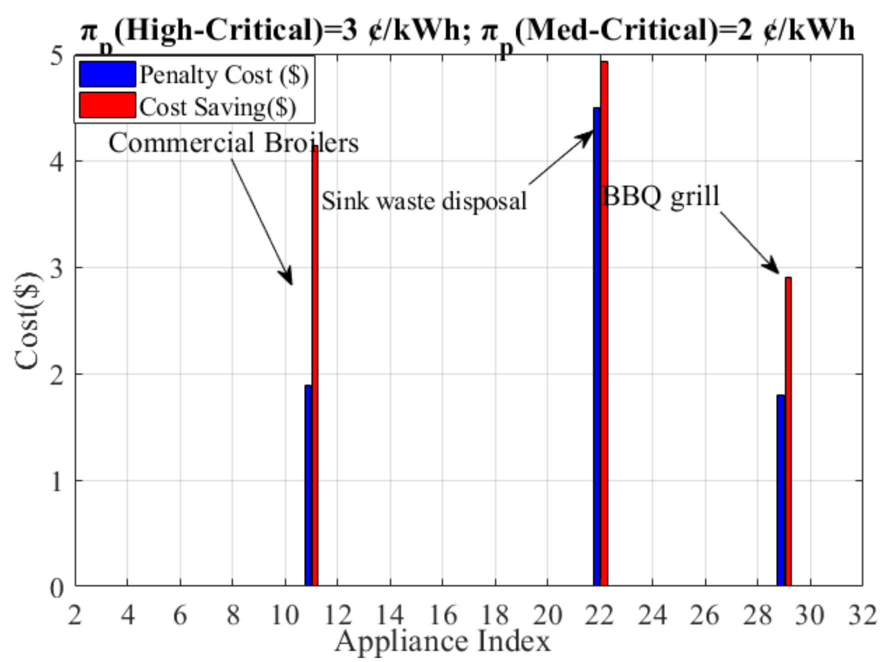

Fig. 36. Cost saving and Penalty Cost at $\pi_p = 0, 2, 3$ c/kWh

installation.it is found that with increasing in the number of customers participated in DSM will tend to smooth the voltage devotions profile and improves the voltage fluctuation caused by load changes. Moreover, when the rooftop PV in highest generated level during the period (from 8:00 am to 16:00 pm), the DSM at $\pi_p = 0$ c/kWh) will help to mitigate the voltage rise problem during these hours.

Fig. 34 illustrates feeder total power loss at different number of customers with the presence of rooftop PV, as we can see with higher DSM participations (note that in this case 100% means the all 30 customers participate in DSM program) will reduce the power loss that occurs during the on-peak price as illustrates in Table 4.2 As its depicted in Fig.39 with DSM (at penalty $\pi_p = 0$ c/kWh) more loads shifted to the time of the PV power generation during the mid-day time and that will mitigate the real power loss.

Last scenario is the comparison of the voltage profiles at the end of the feeder with 30 smart homes participating in the DSM program, this test applied at different value of penalties with the presence of rooftop PV, as it illustrates in Fig. 41 when the value of the π_p increased to 5 and 10 /kWh the voltage less flattering and more fluctuated, also less fewer appliances can shift to the time of the PV powergenerated.

4.8 Conclusion

For radial grid layout comprising 30 buses, we assessed (1) the reduction in the operating cost, (2) PV utilization efficiency, (3) real power loss, and (4) voltage fluctuation. The electricity cost of the residential area show reduction of 37.1%, while the commercial area show reduction of 50.3%, although the customers in commercial building less willing to change their consumption patterns, due to high power rate of the appliances in the commercial load. The reduction in power loss in the commercial area was higher than the reduction of power loss in residential load, as the peak load in the original commercial load profile occur at the time of the peak PV generation period .

Lastly, the results obtain from voltage profile show that when the value π_p increased the voltage less flattering and more fluctuated, also fewer appliances can shift to the time of the PV power generated, in other word, apply DSM without high penalty for load shifting will, reduce the voltage rise, encourage renewable energy consumption, and avoid the overvoltage might occurs due to high penetration level.

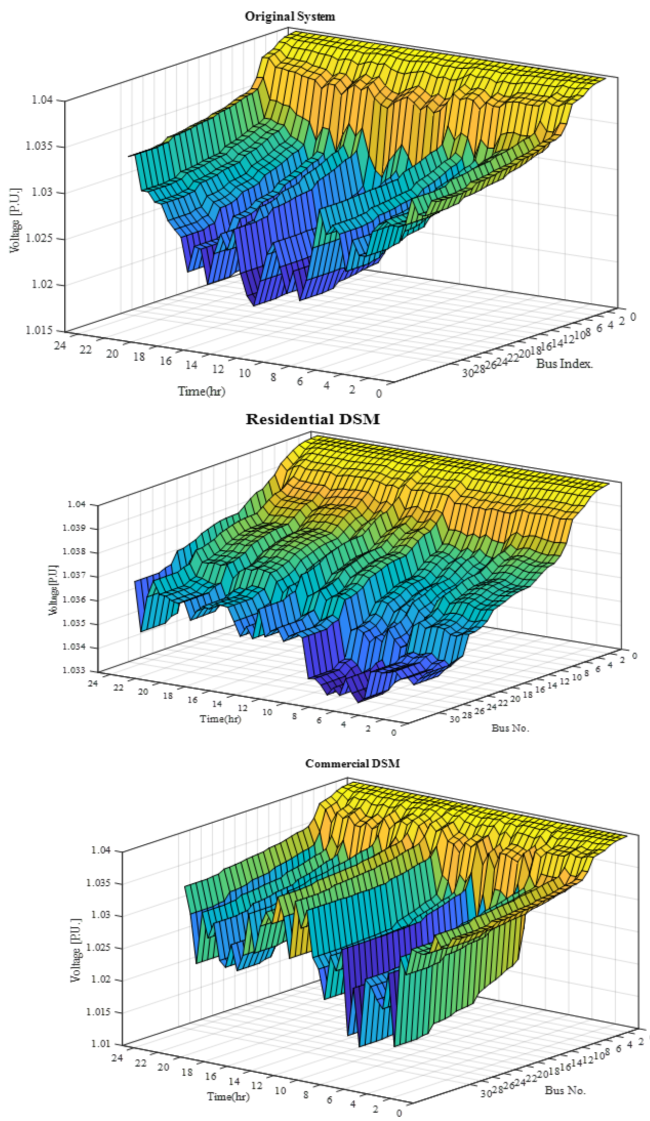

Fig. 37. Voltage profile of Original, Residential, and Commercial

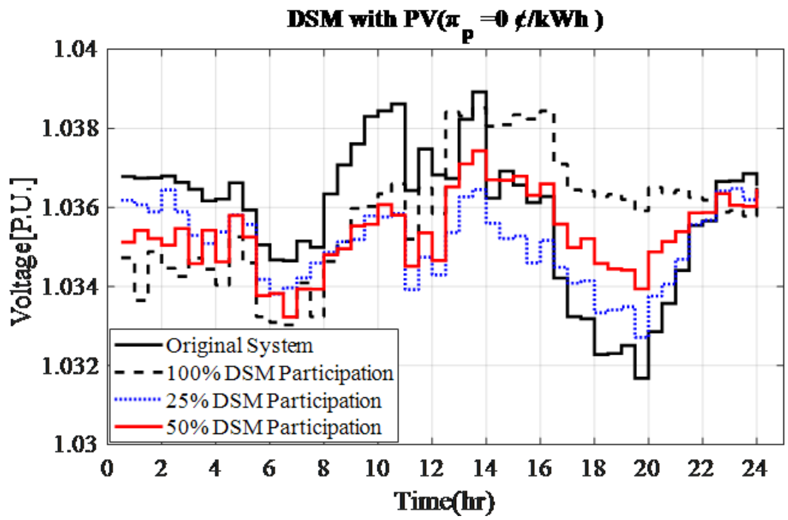

Fig. 38. Voltage profile of the feeder for different DSM Participation level

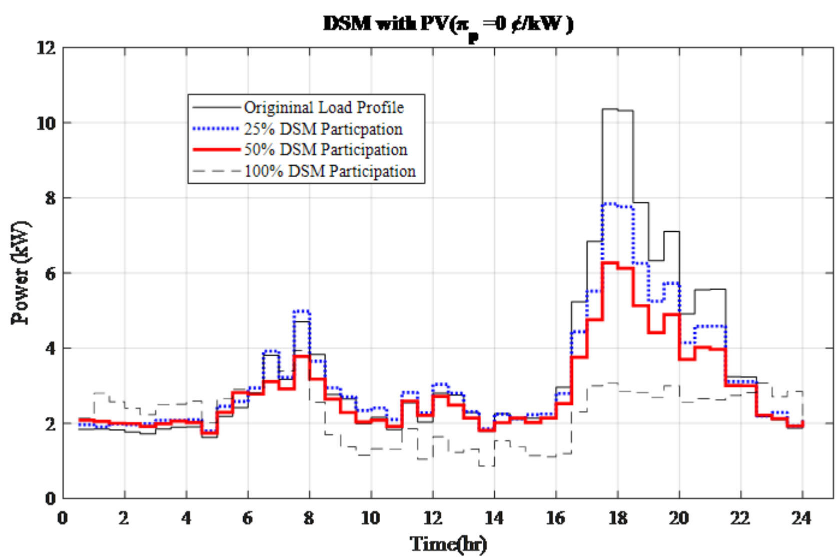

Fig. 39. Power Loss of the feeder at different participation level

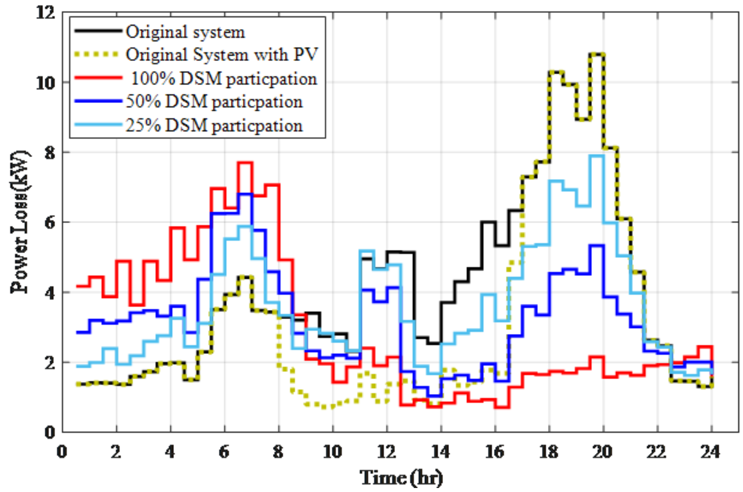

Fig. 40. Feeder power loss for different households DSM Participation level

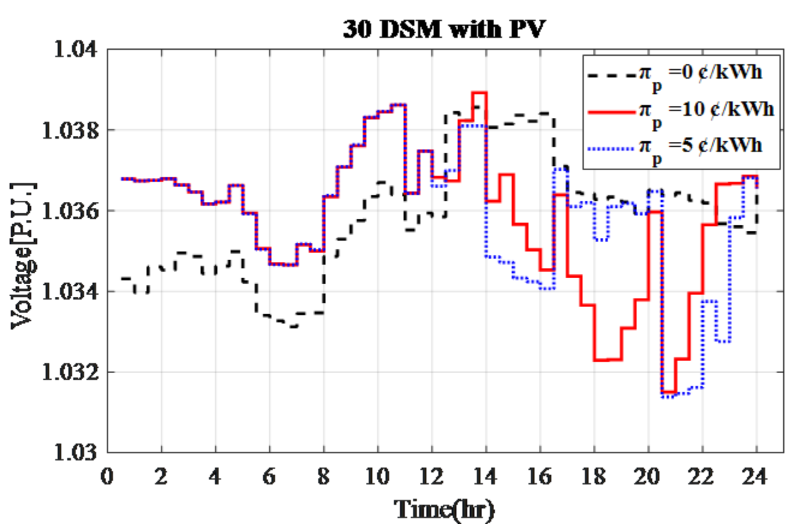

Fig. 41. Voltage Profile with 30 DSM at different penalty

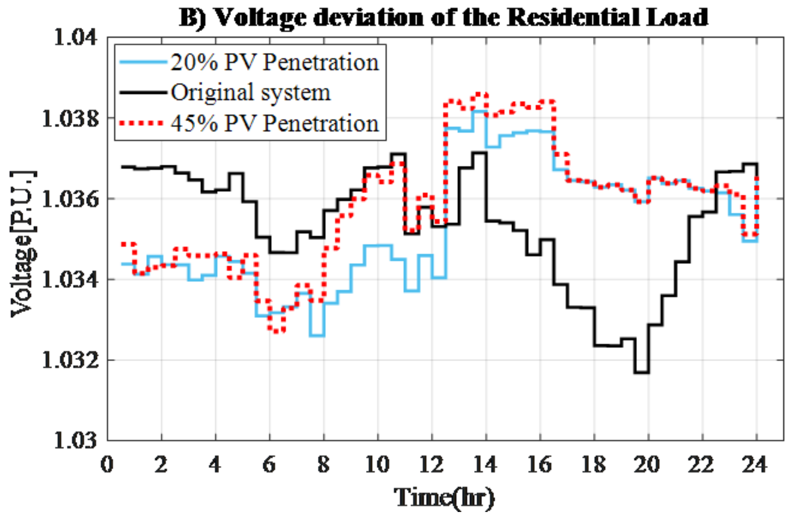

Fig. 42. Voltage Profile with 30 DSM at different penetration level

Table 4.2: Feeder Power Loss in kW for Different Participation Level

	%100 DSM	50%DSM	%25 DSM
DSM with PV	136.5	153.6	172.5
DSM without PV	202.63	199.97	197.33

Table 4.3: No. of Appliances at teach e residential household

Bus No.	Interruptible Appl.	Uninterruptible Appl.	MD (kW)
2	21	7	12.4
3	15	4	15.3
4	17	4	11.8
5	12	4	8
6	19	4	10.5
7	21	4	11.5
8	21	4	14.7
9	21	4	15
10	13	4	15
11	18	4	10.5
12	21	7	11.3
13	15	4	13
14	17	4	8.3
15	19	4	13.6
16	21	4	13
18	19	4	11.7
19	18	4	8.6
20	13	4	11.2
21	18	4	9
22	21	7	10
23	15	4	12
24	17	4	7.2
25	19	4	13.6
26	21	4	14
27	21	4	13.8
28	13	4	15.7
29	18	4	8.6
30	21	7	8.3
31	15	4	13

Table 4.4: Appliances at the commercial Area

Categorization of appliances	index	Appliances	Operation time slot	D_a (30) min	Power (kw)
Baseline Appliances	1	Refrigerator	1 ~ 48	48	22.5
	2	Light	1 ~ 48	48	240
	3	Ceiling fan	1 ~ 48	48	22.5
High-critical π_p =3 ¢/kWh	4	Welding Machine	14 ~ 17	4	109.5
	5	Fan/AC	23 ~ 25	3	109.5
	6	Arc Furnace	24 ~ 26	3	270
	7	Induction Motor	20 ~ 22	2	270
	8	DC Motor	21~ 22	2	270
	9	Ice Machine	12~ 15	4	57
	10	Drum Machine	6~ 9	4	189
	11	Commercial Broilers	21 ~ 24	4	189
	12	Electric drill	39 ~ 42	4	246
Med-critical π_p =1 ¢/kWh	13	Commercial Pizza Ovens	43 ~ 46	4	189
	14	Drop In Hot Food Display Warmers	24 ~ 27	4	105
	15	Water Dispenser	19 ~ 22	4	111
	16	Washing Machine	29 ~ 32	4	96
	17	Sewing machine	39 ~ 42	4	240
	18	Oven	15 ~ 18	4	285
	19	Frying Pan	22 ~ 25	4	246
	20	Dishwasher	36 ~ 39	4	225
	21	Water heater	13 ~ 16	4	225
	22	Sink waste disposal	35 ~ 39	4	225
Low-critical π_p =0 ¢/kWh	23	Gyro Machine	36 ~ 39	4	165
	24	Water Dispenser	28 ~31	4	300
	25	Washing Machine	26 ~ 29	4	270
	26	Gyro Machine	23 ~ 26	4	37.5
	27	Bun Grilling Toaster	35 ~ 38	4	150
	28	Air conditioner	20 ~ 23	4	180
	29	BBQ grill	27 ~ 30	4	180
	30	Meat Slicer	10 ~ 13	4	180
	31	Dough Mixer	30 ~ 33	4	180

CHAPTER 5

DSM ALGORITHMS AND PERFORMANCE COMPARISON

5.1 Introduction

Several demand side management (DSM) techniques and algorithms used to show that by adopting DSM and Time-of-use (TOU) price tariffs, electricity cost significantly decreases, and optimum load scheduling is achieved.

In the first part, this task gives a comprehensive literature review on DSMs that are related to load scheduling, Direct Load Control (DLC), and Demand Response (DR). In the second part, two algorithms are chosen to compare performance in terms of load consumption profile, Photovoltaic (PV) utilization efficiency, and power loss. These algorithms are implemented to find the optimal electric load consumption profile with presence of local PV generation. Furthermore, this work aims to present two approaches for DSM for a residential home. These approaches can be used in response to changes in the price of electricity overtime and in the presence of PV generation to minimize the consumption cost and change the consumption pattern by shifting part of the load to off-peak hours.

In addition, a case study of a single household with a single line is considered under the assumptions of its participation in a DSM program. Results show that the proposed scheduling algorithms can effectively reflect and affect users energy consumption behavior and achieve optimal time distribution of electricity usage. Numerical results show the impact of applying DSM algorithms on total power losses of the feeder.

The major goal of Demand Side Management (DSM) [1] [6] is to efficiently manage loads in such a way that will improve efficiency of the grid, reduce costly generation, and decrease excessive load pressure, and increase power system stability and sustainability. This is done by maximizing system capacity without changing the entire physical infrastructure of the power system.

For instance, researchers in [1] and [2] focused on household DSM, neglecting photovoltaic (PV) utilization efficiency, maximum demand limit, and customers welfare. While load scheduling schemes for scheduling residential loads consumption proposed in [3] [5]. Ref.[4] A combination of DSM and Time-Of-Use (TOU) tariffs significantly decreases the cost of energy with high utilization of PV generation by using a heuristicbased load scheduling scheme as proposed in [3]. These references present a DSM strategy based on load shifting techniques in three services which are residential, commercial, and industrial. The authors consider the priority of the operation time for each appliance by a proposed time delay function to minimize the customer discomfort.

It is worthy to mention here that the authors used the same TOU price for commercial, residential, and industrial; while in our work the electrical price signal used in the residential load differs from the electrical price signal used in the commercial load. In [5], a multi stage optimization for a typical home energy with assumed rooftop solar PV is proposed. The proposed algorithm assumed that the surplus power is injected to the grid with a reward.

The second thing the case study of this paper considered is the appliances preference and no penalty assumed for the shifted appliances. In [6], a residential load scheduling approach is proposed to manage the operation time and to achieve optimal daily usage of DGs. That locally available, genetic algorithm is designed and implemented with a two level of optimization base on the DG-based scheduling and RTP-based scheduling. In our work the objective function minimizes the cost by finding optimal load scheduling and makes the best use of PV generation. Our objective function includes penalty cost and power loss.

References [7] [15] illustrate that DSM can be performed by using Direct Load Control (DLC). Utility companies manage the customer consumption using this method, with the customers appliance controlled by networked technology embedded system. Different type of algorithms are used for DLC. For instance, in [7] and [8], the author proposes an optimization algorithm that can apply with either on or off time to manage and control the load in residential and industrial locales. DLC can also be used to reduce the peak load for large-scale residential demand response implantation [9].

In [10] an optimization technique based on dynamic programming is used to achieve the optimal DLC strategy. A genetic algorithm is used to optimize the scheduling of direct load control (DLC) strategies in [11], and integer linear programming is used for the same problem in [12]. It is notable to mention that some DLC optimization algorithm is used for certain appliances in a household, for example refrigerator and air conditioning in [13] [15]. However, in [5] the developed algorithm covers a variety of appliances in different types of loads; commercially and residentially.

In [16] [24], a Demand Response (DR) program, where users are motivated to be an active participant in managing their loads by reducing their consumption at peak load hours can be the alternative to DLC. In this regard, the most common DR programs include critical-peak pricing (CPP), time-of-use pricing (TOUP), and real-time pricing (RTP). For example, in RTP tariffs, the price of electricity changes at different hours of the day; while the TOUP electricity prices are previously determined and the customer shifts operation time of the load accordingly. In real time pricing, it is difficult and confusing for the customer to respond to the variation in the price every hour. Also, peak load may occur in the low-price time period [18]. Peak load may cause instability in the system; therefore, it would be important to deploy TOUP price with max demand limit as block rates. In fact, this is included in the second optimization algorithm in this paper. Several methods and studies have been implemented over the past two decades in order to minimize the electricity cost-based day head price.

In [19], a DLC algorithm using linear programming is developed; the results showing the electricity cost charged to the customers reduced after participating in this DLC program. Smart pricing adopted in [20] to achieve lower electricity cost proposes a power scheduling for demand response in smart grid system; with results showing the proposed scheme leads to reduction in the peak demand.

In [21], a proposed direct load control based on a linear programming algorithm to manage large number of customers controlling appliances in order to achieve maximum load reduction. Another linear programming model was developed in [22] to optimize system peak period load reduction in commercial and residential load. Heuristic-based evolutionary algorithm (EA) used for energy management in [23], is applied for load scheduling for DLC based on load shifting, this algorithm easily adapts heuristically in the problem.

In this dissertation, a Clonal Selection Algorithm (CSA) method based on the biological immune system and the natural defense mechanism of human body is used. In CSA, the limitation is that the quality of the results depends highly on initial population and probabilities of mutations. Population size selection in the simulation process makes the algorithm converge towards high quality solutions within a few generations. In addition, it is easy to implement. The main difference between Clonal Selection algorithm (CSA) and Particle swarm optimization (PSO) is that PSO doesnt have genetic operators such as mutation, but both CSA and PSO share one aspect which is memory. This means they save the last iterations and update during the optimization process.

According to [24], PSO is similar to the genetic algorithm (GA) as they both are population-based searches; with PSO having memory as important to its algorithm.

Moreover, the optimal solutions in references [25]-[28] to the problem of scheduling household DSM in the presence of PV generation took more precedence. For instance, in [25], an optimal scheduling and controlling approach has been studied which performs scheduling of household appliances and management of local energy resources. A high penetration of distributed generation can lead to problems in low voltage distribution networks. A good review of the literature is presented in [26] that is focused on PV penetration limit due to voltage violation in low-level networks.

In [27], the author proposed an optimization technique base real-time demand response using renewable energy. Optimal load scheduling of households appliances and management of local resource approach assuming a rooftop solar PV. As mentioned in [28] the proposed techniques do not consider the importance of balance between the objectives, energy cost minimization, peak load minimization and user comfort maximization. Also the voltage monitoring part was absent from the constraints. Additionally, the voltage limitation has to be taken into account. This shows that a good DSM algorithm should minimize the electricity cost and maximize the convenience for the customer.

The authors in [29] [38] focused on load scheduling methods based on a day-ahead optimization process to reduce the customers electricity bill. This is achieved by producing or storing energy to lessen their energy purchased from the grid. For instance, in [35], the author proposed a load management technique for air conditioners to enable customers with small air conditioner appliances to participate in various load management programs. This motivates the customer by receiving incentives from the utilities to lower their monthly electricity bills. The work in [36] utilizes smart load management for coordinating the schedule of electric vehicles, taking into account the grid performance such as voltage limit and the total system power loss.

In [37] and [38], the authors proposed model, which aims to find the optimal starting time for charging the battery to minimize the cost delivered by the transformer to minimize distribution charging problems in electric vehicles.

The DSM techniques used in [39]-[42] reduce the peak load of the grid proposed. The idea in this technique is that the load demand information of the user side using the smart power system is provided to the energy provider and the energy price is updated accordingly. The outcomes of these references illustrate that the daily power consumption pattern can be smoother and more controlled through different DSM schemes. For example, the Demand response scheduling under load uncertainty based on real-time pricing in a residential grid is illustrated in [40, 41, and 42]. In these references authors used game theory to obtain the optimal load consumption pattern based on provided price. The authors model the interaction between the energy provider and the customer using this theory.

In [43-49] researchers covered optimization of the performance of the micro grid to make the best use of renewable generation resources and to reduce dependency on grid energy providers. For example, in [43] and [45], an energy management system model proposed including PV generators with storage units. While in [44], the author introduces a residential PV generation energy storage system considering the pattern of daily operation load of the homeowner. The benefit of a storage system in local residential PV installation presents in [46] and [47], wherein the authors study the impact of PV on the quality of the low voltage network.

The works [48] [56] proposed scheduling schemes in a smart grid environment to improve the quality of the power grid and to enable the customer to reshape his production and consumption pattern. Moreover, in these references an optimal residential load scheduling models uses mixed integer linear programming. The proposed model also presents the integration of renewable generation with a battery storage system. The model aims to help the customer to reschedule the appliances to get optimal benefit and to minimize their electricity bill.

The author in [57]-[71] proposed an optimal scheduling technique for residential appliances in smart homes with local PV generation. Results indicate that the proposed strategy has the capability of maximizing the savings in electricity cost.

The work in [72]-[76] studies scheduling of different types of appliances by adopting a dynamic programming-based game theory approach. It is assumed that customers with extra power generation can inject their unused power and receive revenue to reduce their electricity bill.

The previous work in [5], develops an optimization model for a single household DSM model. This model contains a single distribution feeder line supplying a small community of thirteen houses based on a day-ahead household DSM system with local PV generation. The proposed algorithm searches for the optimal solution to the problem of scheduling household DSM in the presence of PV generation under a set of technical constraints such as dynamic electricity pricing and voltage deviation. The proposed solution is implemented based on the Clonal Selection Algorithm (CSA).

5.2 Limitations of the Current Micro grid Literature

Based on the conducted literature review, we review in the rest of this section related current work and discusses their limitations.

1. The DSM programs that have been used (e.g. [33], [34], [41]), proposed an efficient energy management system to schedule the electricity use of appliances to achieve maximum benefits for customers considering all three types of appliances; base, interruptible, and curtailable appliances. The proposed algorithms

do not consider the importance of balance between the objectives energy cost minimization and peak load minimization. While in our work, a DSM model is proposed and mathematical models for the grid, renewable energy resource represented by rooftop PV generation are presented as well as for different type of electrical appliances in different types of loads commercial and residential. This model can effectively minimize the energy consumption cost for day-ahead time.

2. The DSM techniques and algorithms used in [12], [14], and [27] propose a consumption scheduling mechanism for home area load management in smart grid using an integer linear programming (ILP) techniques. Most of them are system specific [12], [13], [10], and some of which are not applicable to practical systems that have a wide variety of independent appliances. Moreover, the techniques were developed in [10], [19] using a linear program. These algorithms and techniques cannot handle a large number of controllable devices from several types loads which have several consumption patterns.

3. The TOUP methods proposed in [38], [40] and [46] were applied to achieve low electricity payment. However, the purpose of the DSM is not only to achieve optimal electricity cost, but also to prevent higher power demand peaks even if the electricity price is low. From this point of view, TOUP applied in these references still has limits causing the demand to be shifted to hours with low electricity price and would lead to a higher peak electricity demand and peak-to-average ratio. During the low-price time, a combination of TOUP with a fixed threshold which represents max demand is necessary.

4. Most DLC optimization algorithms are used for certain appliances in a household, for example refrigerator, air conditioning [34]-[37] which are categorized as

residential load. However, in our work the developed algorithm is expanded to cover a variety of appliances in different types of loads, commercial or residential. Even if they have different characteristic in terms of load profile, electricity price, appliances, and their customer willingness for DSM participation.

5. In [17], appropriate TOUP profiles were used for both residential and commercial loads, where the profiles were different for each load [49]. Our algorithm takes into account the voltage fluctuation evaluation and the power loss of the entire system while optimizing the electricity cost. The goal is to reschedule the energy consumption, considering the day-ahead dynamic electricity price and the real production of the photovoltaic system.

6. According to [24], the limitation of PSO is that quality of the results depends highly on the initial population and the probabilities of mutation. The population size in my work makes the algorithm converge towards high quality solutions within a few generations, while also easy to implement. The main difference between CSA and PSO is that PSO doesnt have genetic operators such as mutation, but both CSA and PSO share one aspect that is they both have memory. This means they save the last iterations and updates during the optimization process. PSO is similar to the genetic algorithm (GA) as they are both population-based searches, where in PSO the memory is important to the algorithm.

5.3 System Model and input Parameters

This section describes the system model with input parameters. This model consists of a single line feeder supplying a small community of thirteen households based on day-ahead pricing. The proposed algorithms used for comparison search

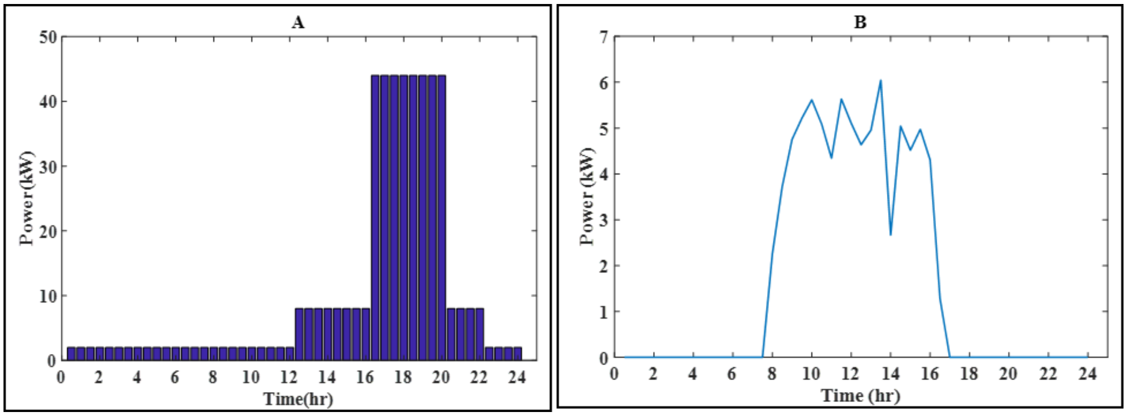

Fig. 43. Figure 6.2: A-Time-of-Use price(/kWh B- PV generated power)

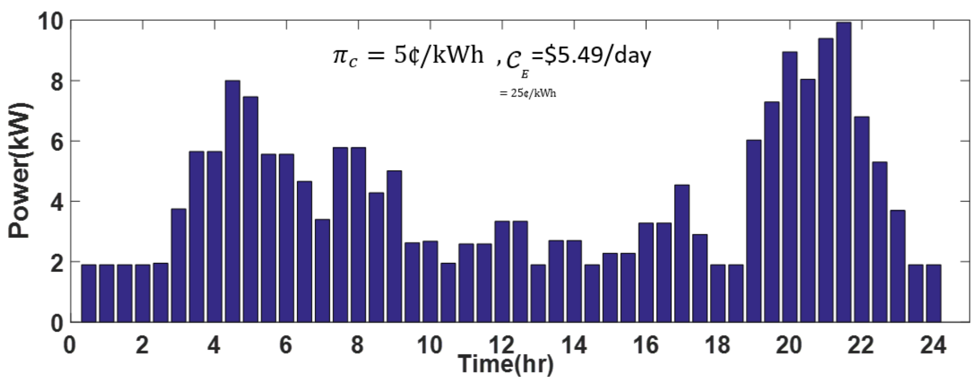

Fig. 44. Figure 5.4: Original Load Profile (kW)

for the optimal solution for load scheduling with presence of local PV generation. The two models used for comparison will have the same input parameters. In other words, the same PV generation profile, the same power consumption profile, and the same electricity price signal. These parameters are used to show the impact of the proposed DSM on a single household with more diversified combination of applicances.

Table 5.1: No. of appliances of the household with the agreed MD

Household Index	Interruptible Appliance No	Uninterruptible Appliance No.	MD(kW)
1	21	7	12.4

5.4 Mathematical Formulation

The work in [4] shows the household DSM model is aimed to minimize the electricity cost by scheduling the on/off status of domestic appliances over the operational periods, considering the dynamic electricity prices, locally available PV generation, and the penalty prices of appliance operation time-shifting which are included to manage the customer inconvenience caused by the proposed DSM algorithms.
The optimization model developed is based on this system. The performance of the DSM algorithms will be tested and compared based on the load scheduled and power loss. First, the model we talk about now aims to make the best of the PV power generation. This reduces the demand on the power grid and reduces the electricity purchased from the grid. The implemented algorithm in this work tries to arrange the operation of the appliance through the day and to find the optimal electric consumptions pattern and hence, reduce the demand during the peak load.
A. The first optimal energy management approach used for the performance comparison [29] formulated as:

$$m\,in\sum_{h=1}^{48} P_{DG}^{h} - P_{must}^{h} - \sum_{a=1}^{m+n} X_a^h \times P_a$$

In the case, the power used by the customer is smaller than the PV generated power, and therefore, no electricity purchase. However, when the demand exceeds the PV generated power the customer needs to reschedule the electricity load to a lower electricity price to reduce the electricity bill.

$\mathrm{x}_a^h = 0, 1, \forall\ a \in \{1\ to\ A\}$

$\beta_a - \alpha_a > d_a$

h_a : is the time that appliance a may operate.

x_a^h : is appliance a on/off condition.

d_a : length of operation time

P_a , Rated power of appliance a $[_a, _a]$Allowable operation time range. $t_a^s tart$, opeation statim slot $t_a^e nd$, operation end time

m, No. uninterruptible appliance

n, No. of interruptible appliance

P_{DG}^h, DG power generation at time h

$P_{flexible}^i$ Total flexible loads consumed at i

RTP_j/RTP_k The time of use pricing at time j or k

P_{must}^i Total baseline loads consumed at time h

C_a^j Energy to buy after the curtailment of appliance a at time j

In the case where the required power demand is smaller than the DG outputs during the operational periods, no electricity purchase is needed.

In the next stage of optimization, the real time pricing scheme (RTP) will be considered

And the optimization problem which is formulated as flows:

$\min\ 0.5 \times \mathrm{c}_a^j \times \mathrm{RTP}_j + 0.5\ \mathrm{c}_a^k \times RTP_k$

$\mathrm{P}_{DG}^i < P_{must}^i + P_{flexible}^i, \forall\ i \in \{1\ to\ 48\}$

$\mathrm{s.t\ x}_a^k = 0, k = [\alpha_a, \beta_a]$

$\mathrm{c}_a^j = (0, P_{DG}^j > P_{must}^j + P_{flexible}^j - x_a^j P_a\ \ or$

$P_{must}^j + P_{flexible}^j - P_{DG}^j, P_{DG}^j < P_{must}^j + P_{flexible}^j - x_a^j P_a)$

$$c_a^k = (0, P_{DG}^k > P_{must}^k + P_{flexible}^k + P_a \quad or$$
$$P_{must}^k + P_{flexible}^k + P_a - P_{DG}^k, P_{DG}^k < P_{must}^k + P_{flexible}^k + P_a)$$

Where j is the time when the energy requirement exceeds the output of DGs after full utilization of DG generation. And k the time slot to which appliance a is shifted. It is important to mention here that each appliance is only periodically scheduled every half an hour.

c_a^j, is energy to buy at the interruptible appliance a at time j, c_a^k, is energy to buy after the increased shifted appliance a at tome k.

In this work, the domestic appliances are categorized into the following typing based on their operation characteristics see Appendix -A.

1. Baseline load: it is the must-run service that needs to be served immediately when it is requested by the residents, e.g. lighting, fridge, computer, television. The energy supply to such must-run services is considered not schedulable and needs to be included into the load demand as the baseline load.

2. Uninterruptible flexible load: it refers to the domestic appliances (e.g. rice cooker, dish washer, washing machine) that require to be operated continuously until completion of the task, and their starting and ending times can be flexibly set.

3. Interruptible flexible load: it refers to the appliances which are allowed to run and can be shut down at any time in the given time interval, e.g. air conditioner, clothes dryer, pool pump, floor cleaning robot, electric radiator.

5.4.1 The Second Approach

The proposed household DSM model is aimed to minimize the electricity cost by scheduling the on/off status of domestic appliances over the operational periods, considering the dynamic electricity prices, locally available PV generation, and the penalty prices of appliance operation time shifting which are included to manage the customer inconvenience caused by the proposed DSM program. Assume that the proposed DSM program is scheduled day-ahead over a 24-h (30 min per slot) period. The decision variables are the operational status of appliances $u_a(t)$ over the next 24 hours and a typical schedule $[u_a(\mathrm{t})]_{A\times T)}$ is a binary (0/1) matrix with following format:

$[u_a(t)]_{A\times T)}$=$[\mathrm{u}_1^1, u_1^2, , u_1^T; u_2^1, u_2^2, u_2^T; ..; u_A^1, u_A^2, ..., u_A^T]$

The objective function and constraints of the second proposed DSM model can be presented as below:

$$\min_{[\mathrm{u}_a(t)]} \mathrm{C}_e + C_p$$

Subject to:

$$\underset{e}{C} = 0.5 \times \sum_{t=1}^{T} P_{load}(t)\pi_e(t) \tag{5.2}$$

$$C_p = 0.5 \times \sum_{a=1}^{A} \pi_p \cdot r_a \cdot \Delta T_a \tag{5.3}$$

$$p_{load}(t) = \max((\sum_{a=1}^{A} r_a \times u_a(t) - \alpha \cdot p_{pv}(t)), 0) \tag{5.4}$$

$$\sum_{a=1}^{A} r_a \times u_a(t) \leq MD \qquad \forall\ a \in \{1\ to\ A\} \tag{5.5}$$

$$\sum_{t=1}^{T} u_a(t) = D_a \qquad\qquad \forall\ a \in \{1\ to\ A\} \tag{5.6}$$

$$u_a(t) = 0 \qquad\qquad \forall\ t < S_a \quad or \quad \forall\ t > \ f_a \tag{5.7}$$

$$\Delta T_a = 1^T \cdot |t_a^{st_{new}} \ - t_a^{st_{old}}| \qquad\qquad \forall\ a \in \{1\ to\ A\} \tag{5.8}$$

$$t_a^{st_{new}} = [t|u_a^{new}(t) = 1]_{1\times D_a} \qquad\qquad \forall\ a \in \{1\ to\ A\} \tag{5.9}$$

$$t_a^{st_{old}} = [t|u_a^{old}(t) = 1]_{1\times D_a} \qquad\qquad \forall\ a \in \{1\ to\ A\} \tag{5.10}$$

$$[v(t)] = f_{AC}\ (P_g(t),\ P_g^{PV}(t),\ P_L^*(t)\ |\,Y_{bus}) \tag{5.11}$$

$$E_{loss} = \sum_{t=1}^{T}\ \sum_{l=1}^{L} |\, i_L^t\,|^2\ R_L \tag{5.12}$$

$$\sigma_v = \sqrt{\frac{1}{TN}\sum_{t=1}^{T}\sum_{i=1}^{N}(v_i^t - \overline{v})^2} \tag{5.13}$$

5.5 Simulations and Numerical Results

As we can see from the first algorithm there is no MD limit on the load consumption. Therefore, the first algorithm tested at MD = 0 kW where the customer is free to shift the load without any concern about the maximum demand limit. Also, the objective function of the first algorithm Eq. 1 neglects the power loss of the feeder. While in the second approach, the algorithm considers that additional cost will be added due to power loss of the system.

Moreover, the first approach has no penalty portion in the objective function. While the objective function takes into consideration the customer inconveniences caused by DSM scheduling which will be translated into additional compensation cost in the optimization objective function. This additional cost represents penalty due to shift of the time operation slots of appliances so that it includes penalty part, C_p. It is important to mention that to make a fair comparison, it is assumed that the amount of C_p equal to zero which means $\pi_p = 0$ c/kWh) when applied to the simulation. In this case, the customer can shift the time slots of the appliances. Results in figs. 45, 46, and 5.8 are from the first algorithm.

As we can see, Fig. 5.6 illustrates the typical load profile of the residential household seen in Fig. 43 with most of the load shifted to the low-price period. The red solid line represents the original energy consumption with two peak loads from 6:00AM - 10:00 AM and from 4:00PM - 10:00 PM while blue bars represent the load scheduled after applying the first DSM approach. Fig.45 also shows that the cost reduced from 18.4 to 4.41 ($/day). However, there is one defect here which is the occurrence of high load during the low-price time between 5- 8 AM. The PV Utilization efficiency was 98.1%. Fig 46 represents the power loss of the feeder as its found equal to 103 kW. Fig. 47 Illustrates the voltage profile of the bus node with the household connected. As we can see there is voltage drop during the peak load time and voltage increased during the maximum PV generated time.

Results in Figs 48, 49, and 50 are from the second algorithm.Fig.47 illustrates the load consumption profile of the households where the red solid line represents the original energy consumption while blue bars represent the load scheduled after applying the second DSM algorithm. Fig.48 also shows that the cost increase to 4.46 ($/day) with just 5/day difference as compared with the first DSM algorithm. However, there are some advantages in the second algorithm.

The first advantage is that there is no overload after applying the DSM algorithm, and the reason is that this algorithm includes a fixed power consumption represented by MD this constraint indicates the MD that the aggregate appliance power of a household cannot exceed at any time; with 12.4 kW assumed as MD in the simulation.

The second advantage is that this algorithm takes into consideration the additional cost due to the feeder loss, which makes the algorithm close to the realistic

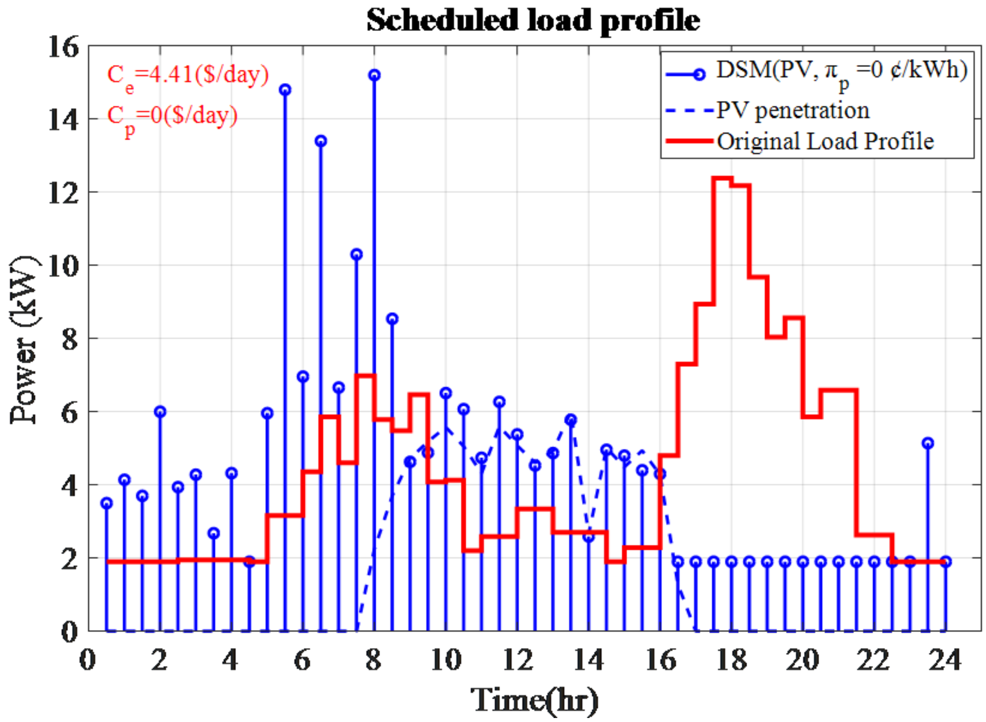

Fig. 45. Scheduled Load Profile

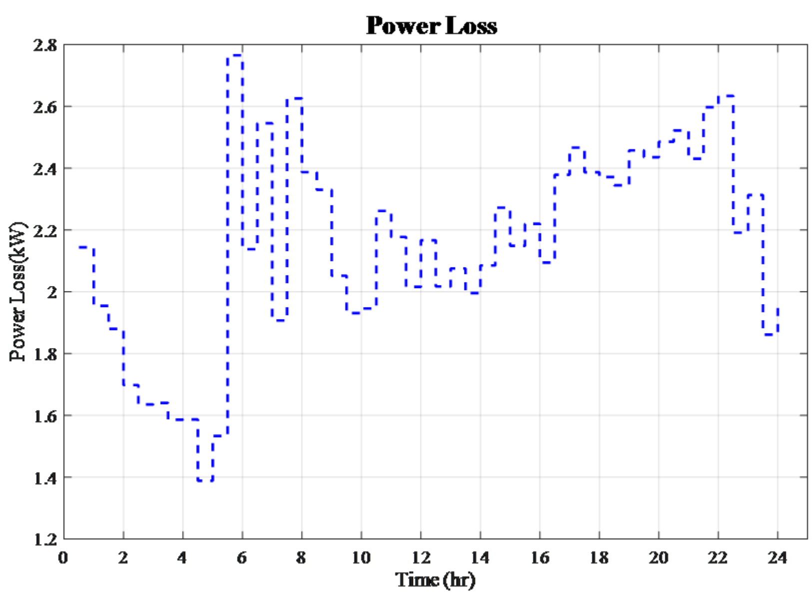

Fig. 46. Power Loss

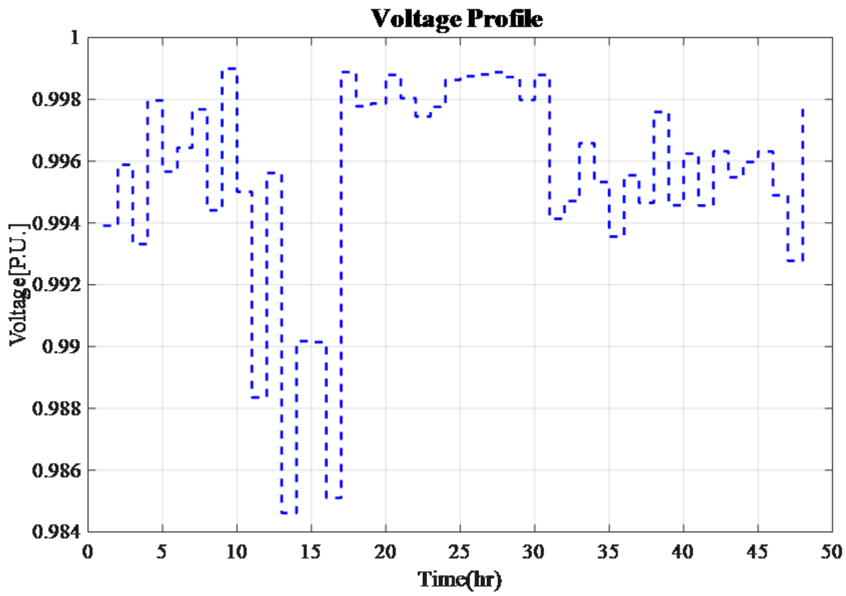

Fig. 47. Voltage Profile

costs. It is also important to mention here that there is one more advantage in the second algorithm and that is the constraints included the voltage limit to maintain the voltage profile swing between the accepted values as illustrated in Fig. 49. The voltage increased from 8:00AM to 4:30 PM. Fig. 50 shows the system power loss after applying DSM algorithm, this figure clarifies the behavior of the line loss with load consumption, the total power loss decreased to 99.3kW as the PV utilization efficiency increased to 98.8%.

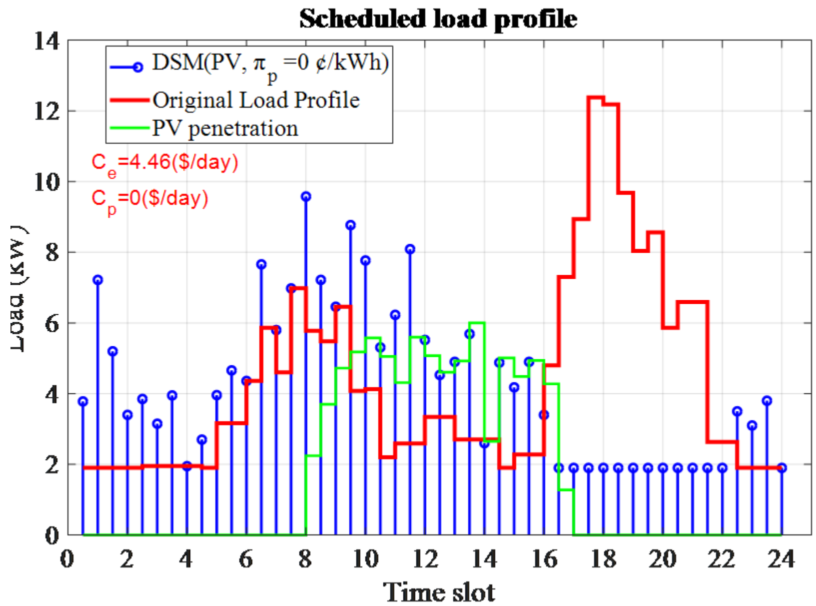

Fig. 48. Scheduled Load Profile

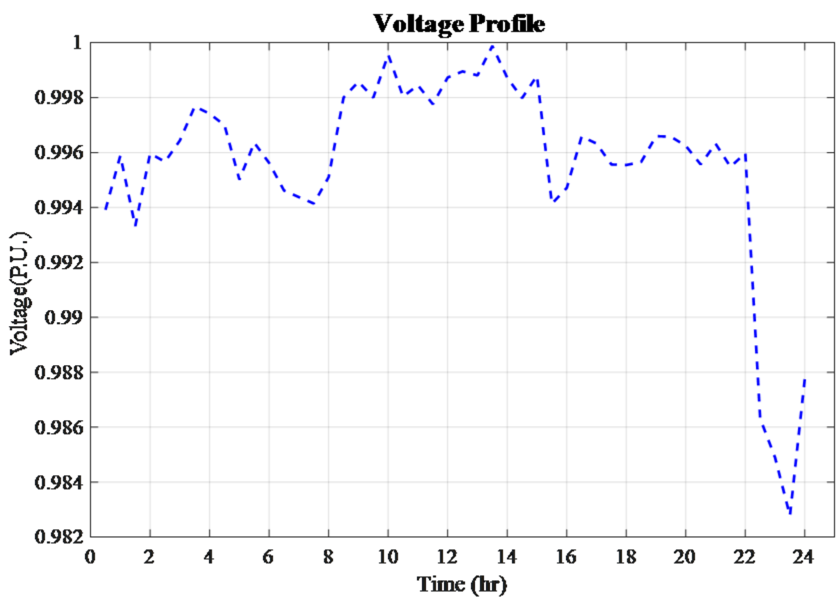

Fig. 49. Voltage Profile

5.6 Conclusion

Several demand side management (DSM) techniques and algorithms has been used in the literature. These algorithms show that by adopting DSM and Time-of-Use (TOU) price tariffs; electricity cost significantly decreases, and optimal load scheduling is achieved. However, the purpose of the DSM is to not only lower the electricity cost, but also to avoid the peak load even if the electricity prices low.

To address this concern, this chapter starts with a brief literature review on the existing DSM algorithms and schemes. These algorithms can be suitable for Direct Load Control (DLC) schemes, Demand Response (DR), and load scheduling strategies.

Secondly, comparison of two DSM algorithms to show the performance based on cost minimization, voltage fluctuation, and system power loss. The results show the importance of balance between objectives such as electricity cost minimization, peak load occurrence, and voltage fluctuation evolution while simultaneously optimizing the cost. The second optimization algorithm has potential to provide more value to the customer in reducing the cost. This is done by evaluating the voltage of the entire system and subsequently avoiding the use the appliances at high peak load during the time when the electricity price periods is high. In other words, a good DSM algorithm should have the objective to minimize the electricity cost for the customer and maximize the customer convenience to handle large number of appliances of several types.

CHAPTER 6

THESIS SUMMARY AND FUTURE WORK

Daily load consumption pattern of electricity in the developed network is controlled by energy management of the consumer side in a way to maintain the load consumption curve within the desired limit by reshaping the electricity demand curve. Utilization of electricity power saving technology, monetary reward, bill rate, decrease the demand during the peak load period instead of adding more generation unites or more distribution and transmission took more attention and concerns of demand side management [32], [33]. By using suitable objective and appropriate methodology of demand side management techniques peak load periods of the electricity consumption pattern can be rescheduled effectively to maintain the reliability of the system and avoid the system instabilities caused due to peak load periods. DSM has multiple necessity in a smart grid system. The advantages of DSM are described below:

1. Electricity cost reduction: Sometimes to meet the peak demand, more high rating generators with high costs are required in the power system. When the peak load demand is shifted from peak to off-peak periods then the grid would tend to be more stable; thus, the cost of the kW/h would be reduced. Moreover, if dynamic pricing is apply then minimizing peak load demand can also help in cost minimization. In additional, DSM plays a key role in preventing costly infrastructure for the power grids, transmission and distribution substations [39].

2. Environmental benefit by employ more energy efficient household appliances can remarkably decrease peak load demand leading to lessen the greenhouse

gas emissions.

3. Reliability and electric network issues: In the smart grid, DSM solve different challenges to keep the system to be more reliable by avoid the peak period demand. Self-maintenance technology of DSM helps to overcome network problems easily without any further disruption in the power grid [6].

The numerical results in chapter two of this dissertation show that an effective demand side management provides benefits not only to the customers but also to the utilities by reducing the peak load demand and overall cost without violating the constraints of voltage deviation and peak load at any time.

The proposed approach may be used in demand side management systems to help household owners to automatically create optimal load operation schedules based on comfort settings of choice and in the presence of dynamic electricity pricing and PV system. The work in chapter two only considers a single photovoltaic system connected to a smart household at the end of the feeder. Simulation results in chapter three work confirm that the proposed scheduling algorithm can effectively reflect and affect users energy consumption behavior and achieve the optimal time of electricity usage.

From the results in chapter four, it is clear that commercial DSM show better effectiveness than the residential DSM and the electricity cost shows 37.1% of reduction, while in commercial load it shows 50.3% decrease, due to high power rate of the appliances in the commercial load so that any small shift will tend to save much higher than the residential appliance.

Also the commercial load profile shows time-alignment with local solar insolation hence the PV generation as well; therefore, commercial DSM usually exhibit better electricity cost savings, higher efficiency of the solar PV usage, larger electric energy loss decreasing, better improvement of voltage fluctuation. In addition, the overall simulation illustrate that decentralized DSM shows a negative effect on grid energy loss. Thus, it is necessary in the future to adopt the coordination DSM optimization for the commercial loads and see how it impacts on the system performance.

Results in chapter five show that the proposed scheduling algorithms can effectively reflect and affect users energy consumption behavior and achieve optimal time distribution of electricity usage. The results also show that these approaches can be used in response to changes in the price of electricity overtime and in the presence of PV generation to minimize the consumption cost and change the consumption pattern by shifting part of the load to off-peak hours.

For the future work, the suggestion is to evaluate the impact of Coordination Demand Side Management (Co DSM) for load scheduling optimization, in this case the implemented algorithm will apply on the entire system [households and the commercials load] as the same time, which is unlike the decentralized DSM algorithm that deals with each load bus individually, the results then need to compare with, comparing its impact on the distribution network operation and renewable integration, in terms of utilization efficiency of rooftop PV generation, voltage fluctuation and real power loss.

The second suggested study the advantage of using small isolated power system of wind and PV profile to be connected to the household to study the contribution of these two sources on the energy cost, this study deals with power scheduling in PV/Wind using the clonal selection algorithm (CSA) to obtain the least cost of electricity. This work can also extended to study the fast dynamics of renewable distributed generation and their impacts on the voltage regulations and transient stability of distribution network.

In addition, it is of interest to find the optimal location and penetration level for distributed PV both from economic and electric stability points of view. Its important to mention that an alternative formulation for the optimization problem using continuous variables need to be applied as a future study.

Lastly, the error correction technique and forecasting methods, instead of using historical data, needs to be assessed. The proposed algorithm can also be applied to the load management problem with respect to the energy storage systems. Further research results will be reported in the future publications.

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Appendix-A

Some algorithms and difference with the proposed model

1. Batchu, and Naran M. Pindoriya. **"Multi-stage scheduling for a smart home with solar PV and battery energy storageA case study."** Innovative Smart Grid Technologies-Asia (ISGT ASIA), 2015 IEEE. IEEE, 2015.

Description:

minimize energy cost:

$\sum_{t=1}^{T} P_{load}^{m}(t)\pi_e(t)F_1$=min($\sum_{h=1}^{H}$ C$_{l,h}L_h$)$/(\sum_{h=1}^{H} C_{L,h}L_h)_m ax$

$Stage-1$

$Minimis\ \ user\ \ discomfort:$

F$_2$ = min($\sum_{a=1}^{A})\lambda_e lec_a).\rho^(DTR_a))/(\sum_{a=1}^{A})\lambda_(elec,a).\rho^(DTR_a))_(max)$

$stage-2:$

$0 \geq S_t \leq 1 DTR_a = (t_a - h_(a,s))/(h_{a,f} - l_a - h_(a,s)).$

Stage one calculate the cost of the overall load, and the denominator calculate the cost taking in to the regard if the customers used the appliance in the preferred time. Second stage is to minimize the inconvenience of the customers,where $\rho^(DTR_a) is the delay time rate.L_h$, is the time of the day and $C_(L,h)$ is the tariff rate. $\lambda_{elec,a}$ $denotes\ thepriority\ of\ appliancea, \rho\ is\ the\ delay\ parameter.$

Similarity and Differences

For similarity in this reference, the customers comfort function included in the objective function, and the difference battery involved as free power. The advantage here is that he algorithm add minimization of battery utilization cost.

2. Ruan, Bingjie, et al. **"Demand response under real-time pricing for domestic energy system with DGs."** Power System Technology (POWERCON), 2014 International Conference on. IEEE, 2014.

Description:

min $0.5\times \mathrm{c}_a^j \times \mathrm{RTP}_j + 0.5\ \mathrm{c}_a^k \times RTP_k$

$\mathrm{P}_{DG}^i < P_{must}^i + P_{flexible}^i, \forall\ i \in \{1\ to\ 48\}$

s.t $\mathrm{x}_a^k = 0, k = [\alpha_a, \beta_a]$

$\mathrm{c}_a^j = (0, P_{DG}^j{>}P_{must}^j + P_{flexible}^j - x_a^j P_a\ \ or$
$P_{must}^j + P_{flexible}^j - P_{DG}^j, P_{DG}^j < P_{must}^j + P_{flexible}^j - x_a^j P_a)$

$\mathrm{c}_a^k = (0, P_{DG}^k{>}P_{must}^k + P_{flexible}^k + P_a\ \ or$
$P_{must}^k + P_{flexible}^k + P_a - P_{DG}^k, P_{DG}^k < P_{must}^k + P_{flexible}^k + P_a)$

To minimize the difference between the DG output and power loads through the day. j is the time when the energy requirement exceeds the output of DGs after full utilization of DG generation. And k the time slot to which appliance a, is shifted. c_a^j, is energy to buy at the curtailment appliance a at time j , c_a^k, is energy to buy after the increased shifted appliance a at tome k.

Similarity and Differences

In this reference the author used two level of optimization base on the DG based scheduling and RTP-based scheduling, while in our work the objective function minimize the cost by finding optimal load schedule and make the best use of PV generation power. Our objective function we include penalty cost and power loss. Moreover, in this reference, constrains not include the voltage boundary, and also the max demand MD limitation for each time slots were not included.

min $\mathrm{C}_e + C_p$

$[\mathrm{u}_a(t)]$

Subject to:

$C_e = 0.5 \times \sum_{t=1}^{T} P_{load}(t)\pi_e(t)$

$C_p = 0.5 \times \sum_{a=1}^{A} \pi_p \cdot r_a \cdot \Delta T_a$

$p_{load}(t) = \max((\sum_{a=1}^{A} r_a \times u_a(t) - \alpha \cdot p_{pv}(t)), 0)$

3. Ahamed, TP Imthias, and Vivek S. Borkar. **"An efficient scheduling algorithm for solving load commitment problem under Time of Use Pricing with bound on Maximum Demand."** Power Electronics, Drives and Energy Systems (PEDES), 2014 IEEE International Conference on. IEEE, 2014.

Description:

$\min f_u = \min \sum_{j=1}^{m} \sum_{k=1}^{k=24} C^k r_j u_j^k + g(\mathrm{udc}_j, u_j^k)$

s.t

$\sum_{k=1}^{k=24} u_j^k = l_j$

$For\ \ j\ 1\ ,\ to\ .mu_j^k = 0,$
$fork \leq S_j or \quad k \geq f_j$
$\sum_{j=1}^{m} \mathrm{r}_j u_j^k \leq M$
$fork\ \ to\ \ 24m\ \ \ from\ \ \ 1\ \ \ to\ \ M.$
$In\, this\, reference\, the\, objective\, function\, is the sum of wo terms.$
$The first\, term\, capture\, he\, cost of energy\, and\, the\, second\, term\, cost\ of\ delay.$
$f(u) = \sum_{j=1}^{m} \sum_{k=1}^{(} k = 24 C^k r_j u_j^k + \sum_{j=1}^{m} \sum_{k=1}^{k=24} \mathrm{g}(\mathrm{udc}_j, u_j^k).$

In this reference the algorithm can be used under with bound on MD. Consumers assume to pay heavy penalty once he exceed the contractually bound Penalty assumed.

Similarity and Differences:

The term g(udc_j, u_j^k) used to capture the delay depend on the decision u_j^k, this can be the similar to our algorithm. Also the MD agreed by the consumer is not restricted, which mean the customer can exceed the amount and pay penalty cost, while in our algorithm we used MD as restricted constraint.

4. Zhao, Zhuang, et al. **"An optimal power scheduling method for demand response in home energy management system."** IEEE Transactions on Smart Grid 4.3 (2013): 1391-1400.

Description:

$\mathrm{P}_a = [\mathrm{P}_a^1, P_{a,}^2,\ P_{a,}^{120}]$

Where P_a^u donates power consumption for appliance a.

In this reference the power consumption scheduling problem as the following optimization problem:

$\min w_1 F_1(P_{scd)} + w_2 F_2(\mathrm{DTR}_a)$
s.t
$\mathrm{t}_a[\alpha_a, \beta_a] DTR_a = (t_a - \alpha_a)/(\beta_a - \alpha_a)$
the reference introduce formula to calculate the delay time rate for each appliances.

$\mathrm{F}_1(P_{scd} = \sum_{u=1}^{120} prC_u(P_{scd}^u).$

$\mathrm{F}_2(DTR_a) = \sum_(A)p^{DTR_a}.$

In this reference, the author introduce scheduling method for home power usage Base on real electric price signal received through energy management system EMS. Where w_1 and w_2 the weights representing the importance of objectives. DTR_a Denotes the delay time rate of appliance a .$\mathrm{P}_scd.Thetotalpowerconsumptionscheduling.\alpha_a$,$\beta_a$ starting and ending operation time respectively.t_a Operation starting time of appliance a. prCu, deotes the energy price at the u^{th} time slot.

Similarity and Differences:

The resolution is 12- minute, 5 time slots. The reference take in to the regard the time delay of the appliances, while no penalty added. The reference also introduce approach for connection the EMS in a HAN. The performance measure cost with and without consider RTP. also in this reference the appliances classify into wo type automatically operated and manually.

5. Logenthiran, Thillainathan, Dipti Srinivasan, and Tan Zong Shun. **"Demand side management in smart grid using heuristic optimization."** IEEE transactions on smart grid 3.3 (2012): 1244-1252.

Description:

$\min \sum_t^N$ (Pload(t)-Objective (t))$Pload(t) = Forecast(t) + Connect(t) - Disconnect(t)$

Connect(t)= $\sum_{k=1}^{D} X_kit.P_1k + \sum_{l=1}^{t-1}\sum_{k=1}^{D} X_ki(t-1)P_((1+t)k)$

Disconnect (t)= $\sum_{g+1}^{t+1}\sum_{k=1}^{D}$ X$_ktg$ P$_1k + \sum_{l=1}^{j-1}\sum_{k}^{D} X_(k(t-1)q)$

s.t

The number of devices sifted cannot be a negative value.

X$_(kit) \geq 0$

The number of devices shifted less the devices available for control.

$\sum_{t=1}^{N} X_kit \leq Ctralabl_(i)$

This reference presents a demand side management strategy based on load shifting technique in three service area residential, commercial , and industrial.

Where $Objective_t$ is the value of the objective curve at time t, and $Pload_(t)$ is the actual consumption at time t. X_kit is the number of devices of type k That shifted fom time step i to t $P_((1+t)k)$ Power consumption at time step t+1. D is he number of device type. j is the total duration of consumption for device of type k. q ,m is the maximum allowable delay.

Similarity and Differences:

This reference proposed demand side management that can handle large number of devices, In three types of area residential, commercial and industrial. The difference with our work is that the same TOP price signal apply for the all areas, while we used two different TOP for commercial and residential. The advantage of this reference was taking into regard the importance of the appliance in their operations time. Simulation results in this wok mainly focuses on the cost minimization with and without DSM. The performance measured the power consumption distributing, and the cost reduction.

6. Ruzbahani, Hossein Mohammadi, and Hadis Karimipour. **"Optimal incentive-based demand response management of smart households."** Industrial and Commercial Power Systems Technical Conference (ICPS), 2018 IEEE/IAS 54th. IEEE, 2018.

Description:

The proposed load shifting technique is mathematically formulated :
min $J(t,p) = |P_C^t - P_O^t|$.
$\mathrm{P}_C^t = \sum_{i=1}^{a} S_i^t p_i + \sum_{j=1}^{\beta} f_j^t p_j - \sum_{k=1} S_k^t p_k$
In this reference the algorithm Take into account the lifestyles of the customers by assume different weight

$\min \sum_{s=1}^{S} d_s^t s.t$

$\mathrm{S}_i^t, f_j^t, S_k^t \geq 0 for \quad all \quad i, j, k$

$\sum_{k=1} S_k^t D_c$

Each device supposed to work for specific duration T^s
$\sum_{n=T_s^s}^{(} T_e^s) x_n^s$
$s = from \quad 1 \quad , \rightarrow \quad S$

In this reference incentive based DR optimization model is proposed to efficiently schedule household appliances for minimum usage during peak hours. Where P_C^t and P_O^t are the value of actual consumption at time t and objective curve at time t. w is weight , d_s^t is the customer discomfort. $\mathrm{D}_c Number of devices k available for control.$$\mathrm{p}_i$, p_j, p_k power of the device type i, j , k . a, Number of shiftable appliances, β represents number of fixed appliances. x_n^s is the binary variable defined for each appliance and for each time slot n N .

Similarity and Differences

In this reference the algorithm take in to the regard that some load may have higher priority and need to shift to appropriate time steps. The results in this reference show an improvement of the power mismatch between the actual and after apply the algorithm. Also the performance measure the energy efficiency and customers bill reduction. The algorithm in this reference involved a hardware devise that can maintain two way communication between the utility and the appliances. Its worth noting that the case study considered 300 households.

7. Shigenobu, Ryuto, et al. **"Optimal scheduling of real-time pricing electrical power market considering participation rate of demand response."** Future Energy Electronics Conference (IFEEC), 2015 IEEE 2nd International. IEEE, 2015

Description:

The objective function is used to minimize the distribution losses PLoss in terms of the node voltages

$\min F(PLB, QLB,) = \sum_t^2 4 \sum_i^N P_L i(t)$

V$_m in \leq \ , _m \leq V_m ax$

$P_f^m in P_f(t)$
$leq P_f^m ax$
$Q_f^m in_f$ (t)≤Q$_f^m ax$

The equations above are the voltage constraints , active power constraints, and reactive power constraints . the state of charging constraints:

B$^{m}in \geq LB(t) \leq B^{m}ax$

PV capacity constraints:

$$\sqrt{(P_{PV}^{2}(t) + Q_{PV}^{2})(t)} \leq S_{P}V(t)$$

The active power flow P_{fG} that is flowing from the grid to customers. P$_{fG}(t) = P_{L}oad(t) - P_{PV}(t)$

V$_{m}in$,V$_{m}ax$ minimum and max appropriate voltage ,$P_{f}^{m}in$,$P_{f}^{m}ax$ The max and minimum active power in the distributed system. $Q_{f}^{m}in$,$Q_{f}^{m}ax$ Represents the max and minimum of reactive power constraints in the system.

Similarity and Differences

In this reference proposed DR with real RTP technique based o real-time pricing to reduce the total demand also this reference include battery and PV as a green sources of energy, While in our algorithm, the surplus power generated by PV assumed to be injected to the grid without reword.

Appendix-B
Computational Complexity

This part calculate the convergence time of the participated households, in case of $\pi_p = 0$ c/kWh. As we can see in Fig.50 the time taken for single household was 53 seconds. While when the Decentralized DSM applied for different number of households (e.g. 4, 8, 12, 16, 20, 24, 28, and 30 households).In this simulation results maximum iteration was 50 and was good to reach the optimum solution in each case. It important to mention here that its assume that the price data provided to the residential area day ahead at 6 pm.

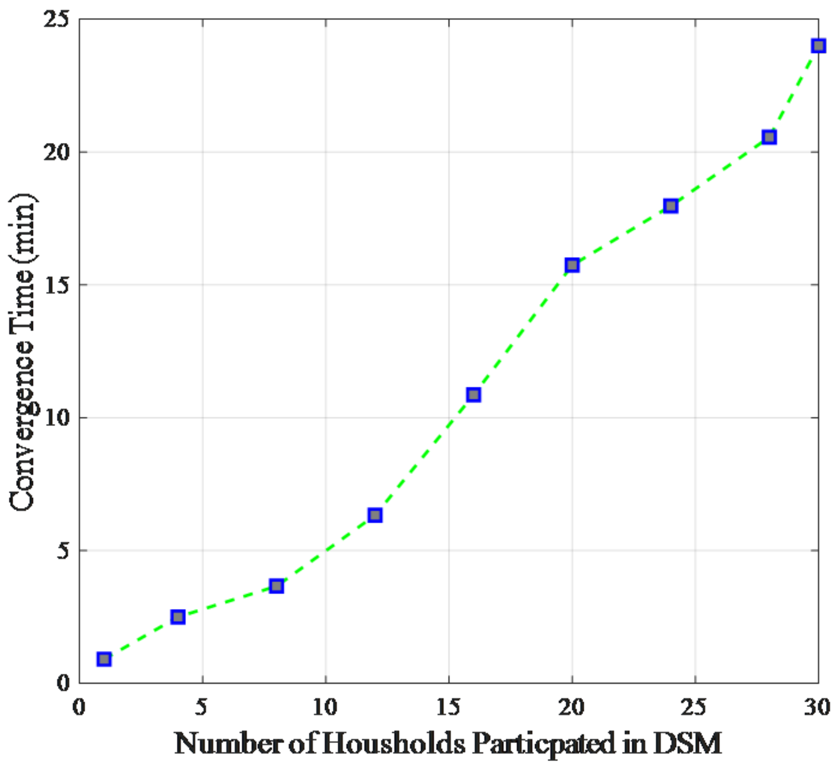

Fig. 50. Computational Complexity for Different Number of Participated Households