DISTRIBUTED SCHEDULING OF ELECTRIC VEHICLES IN A RESIDENTIAL AREA

BY

TUMISANG KEDUETSWE NGUVAUVA

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE (ENGINEERING AND TECHNOLOGY)
SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
THAMMASAT UNIVERSITY
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A Thesis Presented

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Submitted to

Sirindhorn International Institute of Technology

Thammasat University

In partial fulfillment of the requirement for the degree of

MASTER OF SCIENCE (ENGINEERING AND TECHNOLOGY)

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JANUARY 2018

Acknowledgments

Firstly, I would like to thank Sirindhorn International Institute of Technology, Thammasat University for the scholarship for my study and opportunity to do this research. In the same sense of gratitude, I am indebted to my advisor Asst. Prof. Somsak Kittipiyakul who has not only guided me through every step of my research but has also been such an encouragement and never gave up on me.

I would also like to express my gratitude to Assoc. Prof. Dr. Steven Gordon and Assoc. Prof. Dr. Thavatchai Tayjasanant for their valuable time, suggestions and comments during my presentations.

Finally my appreciation goes to my family and friends who have been such a strong support throughout my study.

Abstract

DISTRIBUTED SCHEDULING OF ELECTRIC VEHICLES IN A RESIDENTIAL AREA

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Smart grid technology provides a platform for management of electricity consumption and provision. The management of electricity consumption known as Demand Side Management (DSM) has received a lot of interests from researchers. As the penetration of Electric Vehicles (EVs) increase in the coming future, this becomes a challenge for the electric grid as uncoordinated charging of EVs may cause power outages or even damage the distribution transformers due to overloading of distribution transformers. Therefore, this provides an opportunity for better strategies for management of charging of EVs in order to prevent outages to the electric grid, which can come with a greater risk and expense to energy providers.

In this thesis, we perform a simulation study of the distributed scheduling algorithm, proposed by Chen et al, 2014, in order to coordinate charging of EVs in a residential area. We call the algorithm, Aggregate Power Sharing (APS). We are interested in APS since it provides a distributed EV charging scheduling, requiring minimal message exchanges between a distribution transformer and Energy Management Controller (EMC) in each household and among the EMCs themselves. APS allows EMCs to not violate a pre-specified target aggregate consumption profile.

To study APS, we compare it with a well-known Water-Filling scheduling algorithm and without scheduling. To be realistic, we consider a real typical load profile from an area in Pattaya, Thailand. This area is a pilot smart grid project, planned by the Provincial Electricity Authority (PEA). Our simulation results show that APS provides better fairness than water-filling because each EV is essentially charged at the same rate regardless of their independent state of charge of the EV batteries.

In addition to the study of APS proposed in Chen et al, 2014, we make an improvement to APS by revising the probabilistic strategy to get closer to the target aggregate profile. This is validated by simulation.
Keywords: Load Control, demand response, electric vehicle, distributed scheduling, demand side management.

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Chapter 1

Introduction

1.1 Statement of the Problem

As years go by, new home electric appliances are being made and thus making the electricity demand at residential areas to keep increasing. Electric vehicle (EV) is no exception, as it also uses electricity at home for charging, therefore leading to this increase in electricity demand as society moves towards promoting being eco-friendly. With the high penetration of these, they can cause pressure on the electric grid as the demand can be more than the supply especially during peak hours and consequently cause blackouts which can eventually damage distribution transformers which are very expensive to repair. In any given distribution network, the aim is to make the electric grid as stable and efficient as possible; therefore, effective demand side management is highly required especially if there will be high numbers of EVs which consume a lot of power.

1.2 Objectives of the Study

The main objectives of this thesis are as following:

1. To implement and apply the scheduling algorithm by [4] to schedule the charging of EVs in a residential area, given their arrival and departure time, the current state of charge, their desired final state of charge and as well as the base load profile of a residential area in Pattaya.

2. To assess and analyze the performance of this algorithm by comparing it to the Water Filling algorithm for charging of EVs and as well as when no scheduling algorithm is used.

3. To implement a strategy which can be used in order to fully utilize the allocated power for each house and therefore making the actual power usage as close to the desired local power aggregate.

4. To evaluate the effectiveness of our strategy to fully utilize the allocated power by comparing it to the strategy which was used in [4].

1.3 Significance of the Study

For better demand side management to avoid power outages, damage and overloading to the transformer, a distributed algorithm for scheduling of EVs help to achieve this. This helps to keep actual power usage below the supply of electricity that the transformer can generate. This algorithm ensures that all EVs are charged fairly given an aggregate amount of power to charge, with no electric vehicle more important than the other. This algorithm also takes into consideration other types of load besides the EVs making it suitable to be used in a residential area where they are other appliances in operation.

1.4 Thesis Organization

The rest of the thesis is organized as follows. In Chapter 2, we provide a literature review of some of the important aspects related to this research, starting with the bigger picture, the concept of Smart Grid, and ending with Electric Vehicle charging related research by various authors. Thereafter, we discuss the details of the system model used in this research, the different types of appliances and as well as the different algorithms used for scheduling in Chapter 3. The simulation and discussion of results is given in Chapter 4. Finally, Chapter 5 concludes the thesis and some recommendations are given.

Chapter 2

Literature Review

2.1 Smart Grid

Smart Grid (SG) is the integration of digital technology into the electric grid to enable a two-way exchange of information and flow of electricity between the energy providers and its' customers. This grid can provide the ability to control the ever changing demand of electricity. This is done so the electric grid could be more reliable, stable and efficient. Some of the most important areas in SG are the security of SG, the management and finally the infrastructure available. These are well elaborated in a survey that was done in [5]. SG also promotes eco-friendliness with the incorporation of renewable resources([6], [7]).

The incorporation of digital technology means that communication will be a critical and a necessary aspect of SG and therefore essential to be assessed thoroughly. In [8] this issue of communication has been explored in details. Quality of service has to be of utmost importance. Information must be transmitted in a timely manner in order for changes to be made or areas of concern be attended to in time. Moreover, as SG has different entities which must work together, it must be made sure that these entities have abilities to communicate efficiently. Each entity is as important as the next one. As it is known that companies and factories keep making new electric devices, SG has to be able to accommodate new incoming devices in order to stay valid and efficient. An illustration of the future electric system can be found in Fig. 2.1

Some of the benefits of SG are as follows:

- Consumers have the ability to control their energy use and as a result they can also reduce their electricity bill if they manage their use wisely.

- With the presence of control systems and sensors, if there is any problem at any point in the electric grid, the systems can detect this and specify where the problem could be and the problem could be handled faster, that is, shorter waiting periods during power outages.

- There is less pollution as there is incorporation of renewable resources for production of electricity and due to the use of EVs which are eco-friendly. In general, SG provides a positive environmental benefit .

- Consumers can get full details of their electricity usage instead of just total end of the month bills as there are real-time monitoring devices that can be used.

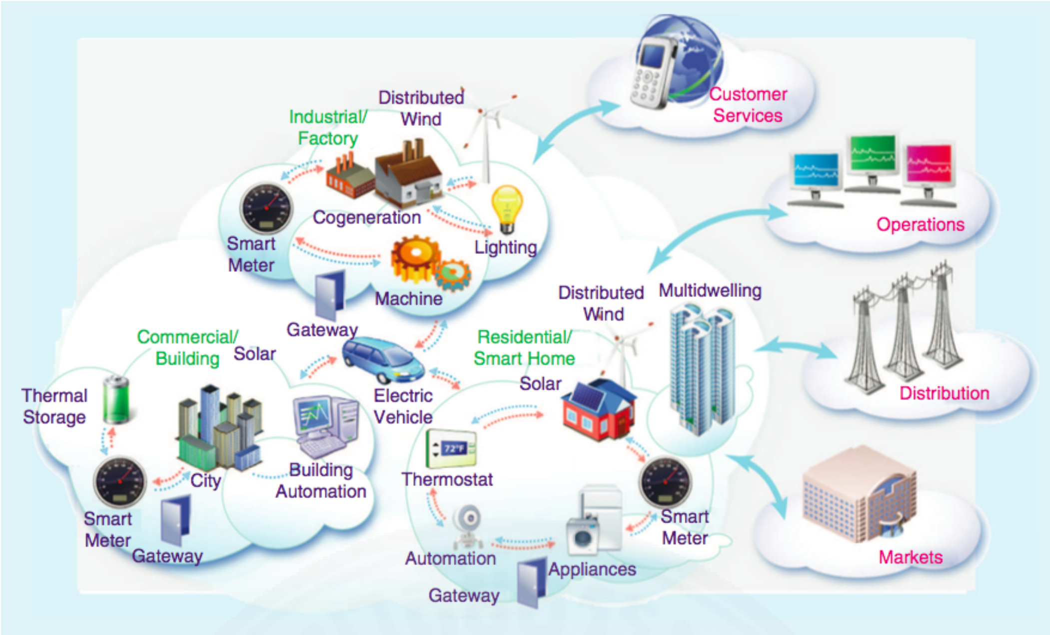


Figure 2.1: Future electic grid [1]

2.2 Demand Side Management

Demand Response provides the opportunity for users and their electric devices to interact with the electric grid in response the changes in demand or electricity prices. All this is done in the form of Demand side Management (DSM). This concept has attracted alot of attention from researchers and industries. It is beleive that DSM can curb some of the problems experienced by the electric grid. DSM aims at reducing power consumption in consumers side (residential areas, offices, industries) and also efficient use of power. Some of the techniques which can be used to shape the demand are found in [9], and are shown in Fig. 2.2.

1. *Peak clipping*: The demand is curtailed during peak time periods.
2. *Strategic conservation*: Efficient use of power, which may include reduction in usage.
3. *Strategic load growth*: Increasing the overall demand strategically.
4. *Flexible load shape*: This may include response to Demand response programs and the flexible load is moved aroundwith certain benefits.
5. *Load shifting*: The demand is curtailed during peak time periods and some demand is shifted off-peak time slots.
6. *Valley filling*: The load is increased to improve the whole system or certain aspects of the system.

Optimization principles have been used in order to manage demand side load making use of the bidirectional capabilities of the SG. This was done with various aims in mind which may be reduction of energy consumption, peak load, cost of production, or consumer electricity costs. Game Theory has been used to tackle DSM ([10],[11] ,[12]), where each user tries to maximise its own benefit which may be to pay the lowest payment of their electricity to the Energy Provider. Users are taken as players in a game and they need to schedule

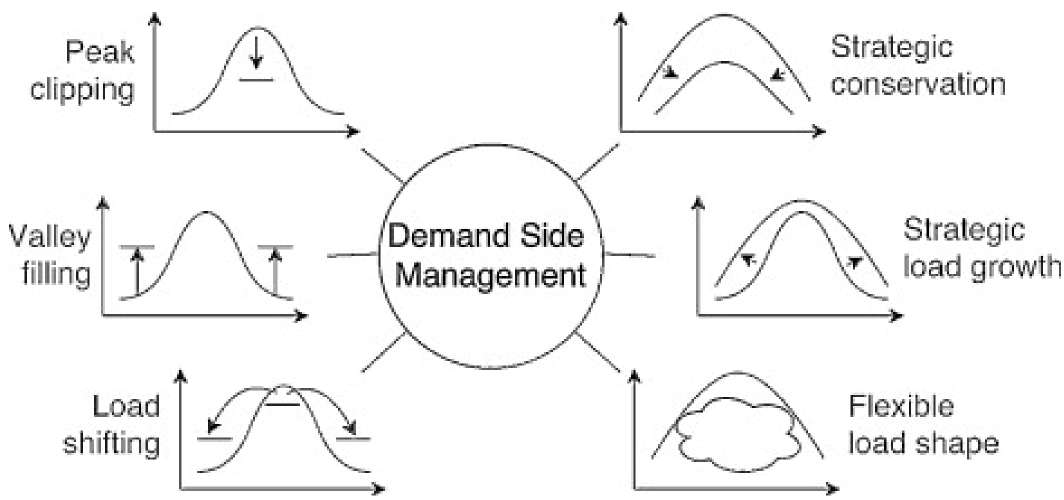


Figure 2.2: Demand Side Management Concept

their appliances strategically. Each user is to choose their best plan of action. Sometimes users maybe reluctant to change the energy usage as a result, various pricing methods have been considered in various literature([13],[14],[15]) as it is an important tool that can encourage the users to use the energy wisely.[15] goes on to mention that with an accurately constructed real-time pricing scheme the following can be acheived: 1) Users have an opportunity to curb their electricity bill , 2) The demand load profiles may be distribued evenly across time of the day, 3) The cost of production of electricity may also be reduced.

DSM is made possible through the use of very important units called *energy controlling devices*. The initial configuration of these units maybe complex but once done they can be very useful and act on peoples' behalf as everything will be automated. These devices are capable of doing one or more of the following functions :

- They can store consumers preferences.
- Gathers weather information, to act appropriately when certain temperatures are detected.
- Monitors power consumption.
- Have ability to check the amount of energy obtained from renewable sources of energy.
- Schedule appliances and switch them on and off at designated times.
- Receive some energy information from energy entities and take proper course of action.
- Essential information can be transmitted to online platforms through the use of Local area network where consumers can access them.

One of the examples to see how this units is useful can be found in [16]. They have implemented an automated system concept (MAHAS) where they have a group of controlling agents working on their own to eventually achieve a global goal. This system has the ability to be reactive when outside influences suggest them e.g, when there is a price hike. In addition to that, this system can plan ahead. The global goal is to keep the consumers energy costs as low as possible while not compromising their comfort.

Table 2.1: Examples of EVs

No.	Car model	Company	Capacity (kWh)
1	Chevrolet Volt/PHEV	GM	16.5
2	Prius Alpha/PHEV	Toyota	1.3
3	Leaf/BEV	Nissan	24
4	Tesla model S/BEV	Tesla	85
5	Fiat 500e/BEV	Chrysler	24
6	Honda Accord/PHEV	Honda	6.7

2.3 Electric Vehicles

Electric Vehicles will in the future increasingly penetrate the society and as a result have started receiving attention from researchers as they pose as a high power consuming device on the demand side. These are vehicles that are powered by an electric motor. With the help of a controller, power is obtained through rechargeable batteries. These batteries can be recharged using electricity from the electric grid. Some of the EVs available in the market can be found in Table 2.1. Due the battery technology used for each car and the type of power source used, each cars charging period may vary. In most cases charging of EVs is most suitable from late hours of the night to early morning and this is done so that the valleys can be filled. It must be noted that sometimes EV batteries can be used as an electricity storage device which can later on dispatch electricity to the grid when needed, and this is one benefit of the EVs to the electric grid. EVs could be fully dependent on being charged with other renewable energy sources as SG allows for this possibility and also to not put pressure on the electric grid. However, the charging of EVs can be complex due to the uncertainity of the amount of electricity that can be produced by these sources.

A well planned integration of high numbers of EVs into the power system can improve the power efficiency and quality, therefore, the management of charging of EVs is necessary in order to avoid power outages and damage of power transformers due to overload. The kind of technology that SG gives room to makes the inflitration of EVs easy. There are Energy Management Controllers that can measure the energy consumptions, analyze and keep this information up to date in real time, as a result this can help in the control of charging of EVs, that is the scheduling of EVs can be done easily.

Some of the impacts of EVs on the distribution grid performance is studied in [17, 3] and a centralized charging schedule is proposed to manage system losses and maximize the profits of the utility company. Similarly, the authors in [18] proposes a centralized charging schedule for EVs with an aim of reducing the utilitys energy cost. Random arrival and departure times of EVs is considered in [19] and a centralized charging schedule is proposed to minimize electric grid overload and also ensure increased grid reliability. One of the disadvatages a centralized charging system is that, there is no privacy for the users, they have to share their EV information which should be considered private. In addition to that, obtaining information from a large number of consumers and making decisions at the utility can become very complex and difficult therefore a proposal to shift optimization to smaller entities (Demand response agents) can be a solution for this. In [20] they have formed a decentralized system that aims at flattening the load curve by scheduling charging of EVs to a pre-specified target before a set deadline. A decentralized charging schedule algorithm is also proposed in [21] which guarantees charge completion and valley filling of the load profile. A dynamic charging approach is used in order to perform a decentralized charging algorithm for a large number of EVs in [22].

Chapter 3

Methodology

In this chapter we explore the system model studied and used in this research and explain all the type of appliances considered and as well as their requirements and constraints. We go on to explain all the algorithms used in this research namely, the Aggregate Power Sharing algorithm and the Water Filling algorithm. The chapter is concluded by an elaboration of our improved Gap Filling method.

3.1 System Model

We consider a system model as illustrated in Fig. 3.1 for a residential area, where there is an Energy Provider (EP) that serves N households. The EP is responsible for providing electricity to the residential area. Each household is considered to have an EV. The distribution network is as shown in Fig. 3.2. Each household is taken to have an Energy Management Controller (EMC), which has profiles of every smart appliance entailing the power consumption, the total run time and the time the appliance is available to be scheduled. The EMC is also responsible for scheduling these home appliances and switching them on and off at the appropriate times.

In addition to that, the EMC can communicate with it's neighbor EMC. They able to give each other their power information, which we discuss the details of, in depth, in the following section. All this communication between these separate entities is made possible through the Local Area Network (LAN). We also assume that the residential area network is connected, that is, there is a path from a house to every house in the system. Time is divided into T time periods, where each time slot is assumed to be 1 hour. For convenience and without confusion, the set $\{1,\ldots,T\}$ is denoted as T. Similarly, the set $\{1,\ldots,N\}$ is denoted as N.

At each time slot $t = 1,\ldots,T$, there is a pre-determined total load Z^t that the power consumption of all the households should not exceed. There are time slots where the demand is greater than this pre-determined load target, which means that some appliances may need to be shifted to some other time slot in the future. To see which appliances can be shifted, we classify appliances into three, similar to in [4]. The different type of appliances and their properties are shown in Table 3.1.

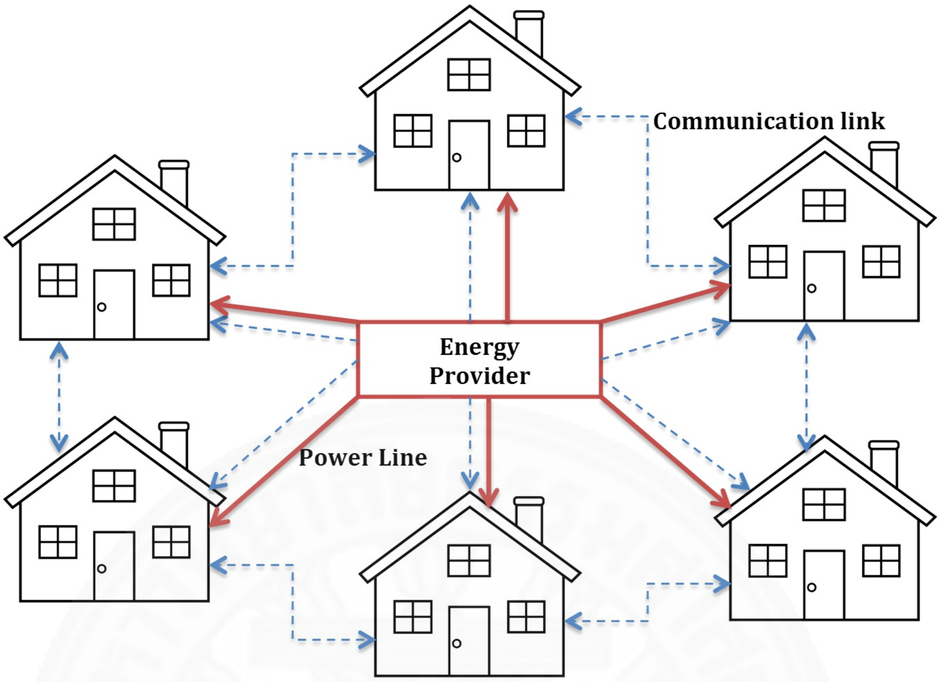


Figure 3.1: System model

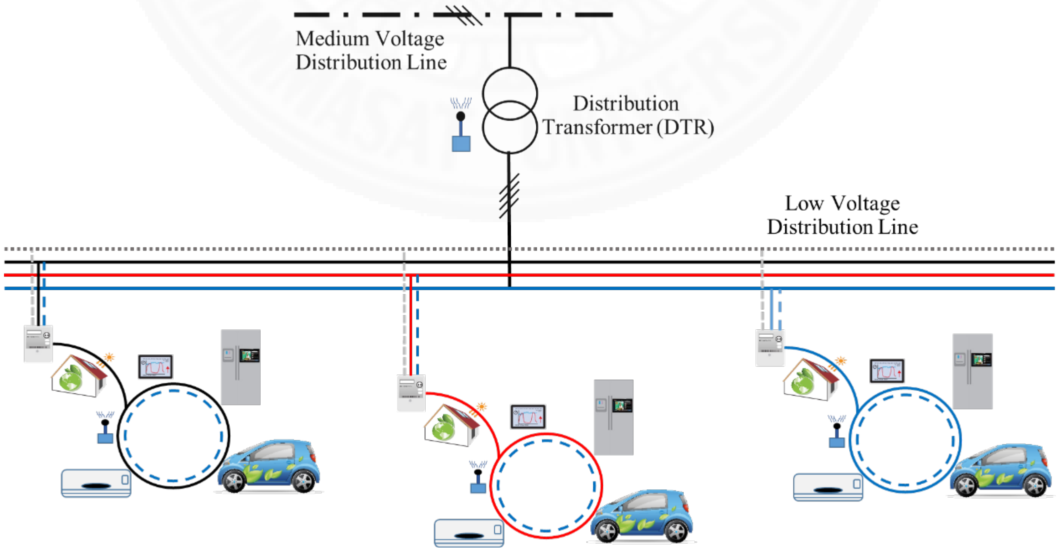


Figure 3.2: EVs in 3-phase distribution network [2]

Table 3.1: Classification of Appliances

Type of appliance	Properties	Examples
Type-1	Non-Shiftable	Fridge, stove, rice cooker
Type-2	Shiftable but non-interruptible	Dishwasher, TV, Washing machine, Clothes dryer
Type-3	Shiftable and interruptible	Electric Vehicles, Energy storage device

Each type is described as follows.

1. *Type-1 appliances (non-shiftable)* : This includes appliances that have strict running times and constant power consumption. These appliances must run immediately they are plugged in.

   We denote the set of type-1 appliances in household $n = 1, \ldots, N$ as X_n. Each type-1 appliance $i \in X_n$ operates in its requested operation time slot $T_i \subset T$ and consumes a constant energy e_i per time slot. That is, the energy consumed by type-1 appliance i in time slot t is

$$e_i^t = \begin{cases} e_i, & t \in T_i \\ 0, & \text{otherwise} \end{cases} \tag{3.1}$$

2. *Type-2 appliances (shiftable but non-interruptible)* : This includes appliances that require continuous operation for a certain period of time. Although the starting time of a type-2 appliance is flexible, the finish time must be before it's deadline. Once turned on, they cannot be turned off until they are done with their complete operation.

   We denote the set of type-2 appliances in household n as Y_n. Each type-2 appliance $i \in Y_n$ has a total runtime, which is the time required to finish the total process of an appliance, denoted as τ_i. The device is allowed to run during time t_i^s, the time it's available to be scheduled, to t_i^e, which is the deadline time. These time specifications are set by the user depending on their preference and lifestyle. To allow the device to finish by the deadline time, it must be scheduled to start at the scheduled start time, t_i^{ss}, before $t_i^e - \tau_i + 1$, that is, $t_i^s \leq t_i^{ss} \leq t_i^e - \tau_i + 1$. Hence, the operation time slots are $T_i = \{t | t_i^{ss} \leq t \leq t_i^{ss} + \tau_i - 1\}$.

   If the device consumes a constant energy of e_i during operation, the consumed energy at time t is $e_i^t = e_i$ for $t \in T_i$ and 0 otherwise.

3. *Type-3 appliances (shiftable and interruptible)* : This type entails appliances that can be shifted to different time slots and they can be operated at non consecutive time slots. For this type of appliances we focus on the Electric Vehicle(EV). An EV can be charged at different rates within the allowable rate of charge. The charging must happen during some start time and end time but can be interrupted. These times can be considerd to be arrival and departure times of an EV, which are provided by the user. There may be target state of charge (SOC) that must be achieved before the end time. The state of charge is the amount of energy stored in the EV's battery. We denote the set of type-3 appliances in household n as Z_n. Each type-3 appliance $i \in Z_n$ has an initial SOC, denoted as ISOC_i, an arrival time t_i^a, a departure time t_i^d, and a target

SOC, denoted as TSOC_i, which is usually the full battery capacity. The minimum and maximum rate of charge is denoted by e_i^{min} and e_i^{max}, respectively. At time t, the energy charged to the EV is e_i^t where

$$v_i^t e_i^{min} \leq e_i^t \leq v_i^t e_i^{max} \tag{3.2}$$

and $v_i^t = 1$ if the EV is charged during time t and 0 otherwise. We also must make sure that the battery is not overcharged, i.e.,

$$\mathrm{ISOC}_i + \sum_{t=t_i^a}^{t_i^d} e_i^t \leq \mathrm{TSOC}_i \tag{3.3}$$

If the system works properly, where electricity supply is more than demand and the scheduling is done efficiently, then we expect equality in (3.3), where the EV is finally charged to its target SOC at the departure time.
So in summary, for charging of EVs, each EV is specified by the following six parameters:

(a) Initial state-of-charge

(b) Target state-of-charge

(c) Arrival time

(d) Departure time

(e) Minimum rate of charge

(f) Maximum rate of charge

3.2 Aggregate Power Sharing (APS) Algorithm

As mentioned in the above section, there is a desired target power aggregate load profile Z^t, for each time slot t for the whole residential area. There are various ways in which this Z^t may be found and one way is from prediction of historical power usage data and also taking into consideration the distribution transformer and its efficiency output power. The APS algorithm proposed in [4] goes through three main stages at every timeslot t: Load Information Update Phase, Target Update Phase, and Admission Control Phase.

3.2.1 Load Information Update Phase

At the beginning of each time slot t each EMC gathers all the power request information for the smart appliances in the households for that particular time slot. There are two classifications of the load requests that the EMC determines namely:

- *Fixed loads*: These entails load the load that must be served during that time slot t. They are a priority. They are the type-1 appliances that must be in operation during that time slot t and type-2 appliances that have been running from the previous time slot t and have not finished their operation.
- *Flexible loads*: These are type-2 appliances that have not started running and type-3 appliances (EVs) that are available to be scheduled for operation. The starting time of type-2 appliances is shiftable and the charging power of EVs is adjustable.

The total fixed and flexible loads in household n at time slot t is denoted as c_n^t and f_n^t, respectively.

3.2.2 Target Update Phase

In the phase the total fixed load for all households is denoted as follows:

$$C^t := \sum_{n=1}^{N} c_n^t \tag{3.4}$$

and the total fixed load for all households is expressed as following:

$$F^t := \sum_{n=1}^{N} f_n^t \tag{3.5}$$

It must be noted that $(C^t + F^t)$, which is the requested demand at time slot t, can be greater than the desired target load profile Z^t. This means that some flexible loads must be shifted to other time slots or those of which can reduce the power consumption can do so in order to be able to stand a chance at running in this time slot.

When the requested demand is more than the target demand, each EMC can serve only a common reduction factor r^t, where $0 \leq r^t \leq 1$, of the requested flexible load. That is, it can serve only the *target power consumption* q_n^t where

$$q_n^t := c_n^t + r^t f_n^t \tag{3.6}$$

The reduction factor r^t is chosen such that the sum of the power consumptions for all households is equal to the target load profile, that is,

$$Z^t = \sum_{n=1}^{N} q_n^t \tag{3.7}$$

However, since from (3.4)-(3.6),

$$\sum_{n=1}^{N} q_n^t = \sum_{n=1}^{N} (c_n^t + r^t f_n^t) = C^t + r^t F^t, \tag{3.8}$$

the reduction factor r^t is calculated easily as

$$r^t = \frac{Z^t - C^t}{F^t} \tag{3.9}$$

which is the ratio of the available target load profile for the flexible load (excluding the fixed load), $Z^t - C^t$, and the requested aggregate flexible load, F^t.

Note that r^t in (3.9) could be negative or greater than one; hence, it is more appropriate to say

$$r^t = \left[\frac{Z^t - C^t}{F^t}\right]_0^1 \tag{3.10}$$

where

$$[x]_0^1 := \begin{cases} x & 0 \le x \le 1 \\ 1, & x > 1 \\ 0, & x < 0 \end{cases} \tag{3.11}$$

If $Z^t - C^t$ is negative, the target load profile is violated even with running the fixed load alone. This could be because the load profile is very tight and decision to run type-2 appliances which cause commitment in subsequent time slots needs to be optimized over time.

Average Consensus Algorithm

Since each EMC receives the target demand for the whole area at time slot t, Z^t, each EMC is responsible for determining the flexible load reduction factor r^t and it can do this by determining the total fixed load (C^t) and flexible load (F^t) of the whole system. With the knowledge that each EMC can communicate with its neighbor EMC, the above unknowns can be known using the *average consensus algorithm*, iteratively. The average consensus algorithm is key in making APS a distributed algorithm by not requiring a centralized scheduler. The average consensus algorithm works as follows;

At every k^{th} iteration $\bar{c}_n^t(k)$ and $\bar{f}_n^t(k)$ will respectively converge to $c^{t*} = (1/N)\sum_{i \in N} {c_n}^t$ and $f^{t*} = (1/N)\sum_{i \in N} {f_n}^t$ with an proper step size β. All this is done according to the following iterative linear updates;

$$\bar{c}_n^t(k+1) = \bar{c}_n^t(k) + \beta \cdot \sum_{j \in B_n} [\bar{c}_j^t(k) - \bar{c}_n^t(k)] \tag{3.12}$$

$$\bar{f}_n^t(k+1) = \bar{f}_n^t(k) + \beta \cdot \sum_{j \in B_n} [\bar{f}_j^t(k) - \bar{f}_n^t(k)] \tag{3.13}$$

The initial values are as follows; $\bar{c}_n^t(0) = c^t{}_n$ and $\bar{f}_n^t(0) = f^t{}_n$. B_n is a set of neighbors of EMC n. $\bar{c}_n^t(k)$ and $\bar{f}_n^t(k)$ will converge to $C^{t*} = (1/N)\sum_{i\in N} c_i^t$ and $F^{t*} = (1/N)\sum_{i\in N} f_i^t$ respectively with proper step size β.

Thereafter r_t can be computed using 3.9. Finally each EMC can know how much power is available for scheduling.

3.2.3 Admission Control Phase

Seeing that the household target power consumption $q_n{}^t$ is now known, the EMC n is tasked with making admission decisions as to which appliance from type-2 to turn on and which type-3 appliance(EV), if any, to charge and at what level of power.

Let the set Y_n^t denote the set of type-2 appliances requested to run during time slot t and the set Z_n^t denote the set of EVs that still requires charging.

The EMC's admission problem is expressed as

$$\text{maximize} \sum_{i\in Y_n^t} y_i e_i + \sum_{j\in Z_n^t} z_j \tag{3.14}$$

subject to

$$c_n^t + \sum_{i\in Y_n^t} y_i e_i + \sum_{j\in Z_n^t} z_j \le q_n^t \tag{3.15}$$

$$y_i \in \{0,1\},\;\; i \in Y_n^t \tag{3.16}$$

$$v_j e_j^{t,min} \le z_j \le v_j e_j^{t,max},\; j \in Z_n^t \tag{3.17}$$

$$v_j \in \{0,1\},\;\; j \in Z_n^t \tag{3.18}$$

where $y_i = 1$ means the type-2 appliance $i \in Y_n^t$ is scheduled to turn on at power consumption e_i, while $v_j = 1$ means EV $j \in Z_n^t$ is scheduled to be charged at power level z_j between the minimum charging level $e_j^{t,min}$ and the maximum level $e_j^{t,max}$. Constraint (3.15) ensures that the EMC tries to operate as close as possible to the target power consumption but not violating the target power consumption . The admission problem is a mixed integer linear programming (MILP) which could be solved efficiently, due to its small size of decision variables and constraints, using solvers such as CPLEX or glpk.

3.3 Water Filling (WF) Algorithm

We compare the APS algorithm to the Water Filling (WF) algorithm, for centralized or distributed charging scheduling of EVs. Water filling or water pouring is a well-known algorithm in information theory where most power is distributed through the channel with the least noise. (for example, see [20]). In [2], a centralized version of WF to schedule charging of EVs. WF can be done in a distributed manner as well.

In the centralized WF, at every time period t each household gives the EP the information on the power demand of household appliances that are to run at that time period and the SOC of the EV that is requesting to charge. Taking into consideration the non-EV power requirements of all households and the desired target for that time period, the EP calculates how much power is left that can be distributed to the charging of EV's.

The aim of WF is essentially to charge the EVs that have the least SOC first before granting other EV's with higher SOC to charge. To be specific, let us first ignore the maximum and minimum charging rates and the target SOC, suppose there is total power of P for charging all EVs (one EV per house) at time t, WF distributes the charging power z_n to EV n with state of charge SOC_n^t at start of time slot t such that the aggregate charging power is P, i.e., $\sum_{n=1}^{N} z_n = P$. There exists a water level $\alpha \geq 0$ such that

$$z_n = \max(0, \alpha - \mathrm{SOC}_n^t) \tag{3.19}$$

for all $n = 1, \ldots, N$. The name water-filling comes from the analogy that suppose there is a two dimensional well with uneven bottom. The well's bottom consists of N levels where each level n is 1 meter wide and SOC_n^t high. We pour water of P meter square to this well. The water level will be at level α and the height of the bottom with level n is $z_n = \alpha - \mathrm{SOC}_n^t$ if this value is nonnegative, and $z_n = 0$ otherwise. The level α is such that the water in all N bottom levels is equal to the amount of water poured in, i.e., $\sum_{n=1}^{N} z_n = P$.

Note that with the maximum and minimum charging rates and the target SOC factored in, z_n must not violate these bounds and hence the total power P may not be fully utilized. More specifically, the complete centralized water-filling problem at time t can be formulated as a convex optimization problem (see, e.g., [20]).

In summary, the optimization that takes place during WF algorithm is as follows;

$$\max \sum_{n=1}^{N} \log\left(1 + \frac{z_n}{SOC_n^t}\right) \tag{3.20}$$

subject to

$$\sum_{n=1}^{N} z_n \leq P \tag{3.21}$$

$$v_n e_n^{min} \leq z_n \leq v_n e_n^{t,max},\ n = 1, \ldots, N \tag{3.22}$$

$$v_n \in \{0, 1\},\ n = 1, \ldots, N \tag{3.23}$$

where $e_n^{t,max} = \min(TSOC_n - SOC_n^t, e_n^{max})$, i.e., the battery should not be overcharged more than the target SOC, $TSOC_n$, and more than the maximum charging rate e_n^{max}.

3.4 Gap Filling

When APS scheduling is used there is a difference in actual power used, A^t and Z^t, desired target demand at some timeslots even when there are appliances that have not run, but have requested to run. This gap is caused by appliances of type-2 which use constant power for operation. Depending on how much power is available for scheduling some type 2 appliances may not be able to run at all thus creating a gap between target demand Z^t and Actual consumed power, A^t.

In order to find if there is a gap, δ^t we define the gap as follows,

$$\delta^t = \begin{cases} |Z^t - A^t|, & \text{if } C^t + F^t > Z^t \\ 0, & \text{otherwise} \end{cases} \tag{3.24}$$

3.4.1 Gap Filling 1

In an attempt to fill the gap above, it was proposed in [4] that where there is a gap, the ${q_n}^t$ to be used during optimization be increased a bit before the EMC solves admission optimization problem. With probability p, the new target consumption is $\tilde{q_n}^t = {q_n}^t + {P_n}^{max,t}$, where ${P_n}^{max,t}$ is the power request value of the highest power demanding appliance. The values of probability p has to be chosen carefully as this may cause a lot of violation of the desired target if not chosen carefully. Take note that even with the ${q_n}^t$ altered it does not guarantee this appliance i will run as the EMC still has to do the scheduling.

3.4.2 Gap Filling 2

On the contrary, we propose that the attempt to fill the gap should be done after the EMC admission phase in a timeslot where there is a gap, taking into consideration all the appliances that were scheduled not to run in that timeslot from the result of the admission optimization. Firstly we determine which appliance has the least power demand request ,and we consider the gap that is available for user n, that is, ${\delta_n}^t = {q_n}^t - {a_n}^t$, where ${a_n}^t$ is the actual demand to be used from the results of the EMC admission stage. We then assign probability $s = {\delta_n}^t / e_i$, where e_i is power demand of the appliance i with the least power demand. Thereafter we draw k from a uniform distribution, $0 \leq k \leq 1$. Finally, if $k < s$ run appliance i if not, it still remains not scheduled and has to wait for the next time slot. In our proposed method we do not need to worry about choosing the right probability in which the appliance can run since its totally dependent on the available gap, ${\delta_n}^t$ and e_i, the power consumption of the appliance. This makes it easier and fills the total area gap, δ^t better, as to be shown in the following section.

Chapter 4

Simulation Results and Discussion

For the following scenarios, the simulations were implemented in python and pyomo modeling language. The mixed integer optimization problem in APS is solved using CPLEX solver while the convex optimization problem in WF is solved using *cvxpy*.

4.1 Four households with only EV Load

We consider 4 households, each house having an EV, to see how APS and WF works. For illustration purposes and convinience a 24 hour time period is used, from 12 noon to 11 am the following day, where each time slot is assumed to be 1 hour. Table 4.1 displays the arrival and departure times for the respective EVs and as well as their initial state of charge. We consider the desired demand target to be $Z^t = 8$ kWh since we are only dealing with EV load with no type-1 and type-2 appliances. The minimum and maximum charge are 0 kWh and 3 kWh respectively. The battery capacity of each EV is 24 kWh.

Table 4.1: EV information for 4-household scenario

Household *No.*	**Initial SOC** *(kWh)*	**Arrival Time**	**Departure Time**
1	20	18:00	7:00 (next day)
2	10	18:00	7:00 (next day)
3	10	18:00	7:00 (next day)
4	15	18:00	8:00 (next day)

In Fig. 4.1 we see the power consumption of each EV when there is no scheduling involved. It can be observed that each EV starts charging immediately they are plugged in and they all consume maximum power of 3 kWh each. Depending on the initial state of charge each EV obtains maximum power of 3 kWh until they finish charging or require less power to reach their full capacity. At 18:00 when all EV charge at maximum rate, the total power consumption is seen to be 12 kWh which is above the required desired limit of 8 kWh. This violation continues until 21:00.

In Fig. 4.2 Power is shared equally unless for some EVs that are almost full and can only be charged as much as can handle. Take note that the power allocated is of the same ratio.

In Fig. 4.3 it can be observed that the EV with the lowest SOC is charged first and then if power is still available the next EV with the least SOC is charged. Looking at user 1's EV, though available for charging from 18:00, its deferred from charging until a later stage because it has a higher SOC.

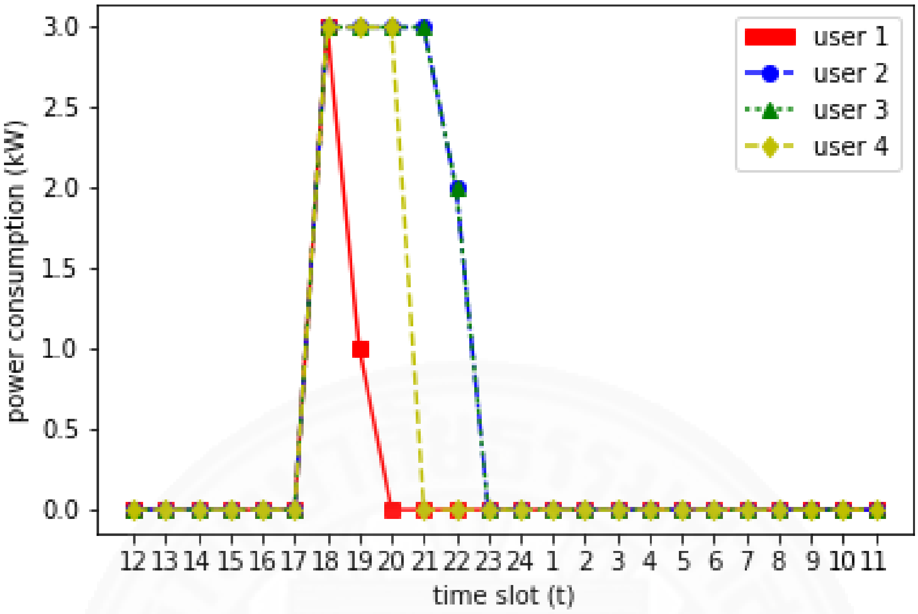


Figure 4.1: Actual Power consumption per user, no scheduling

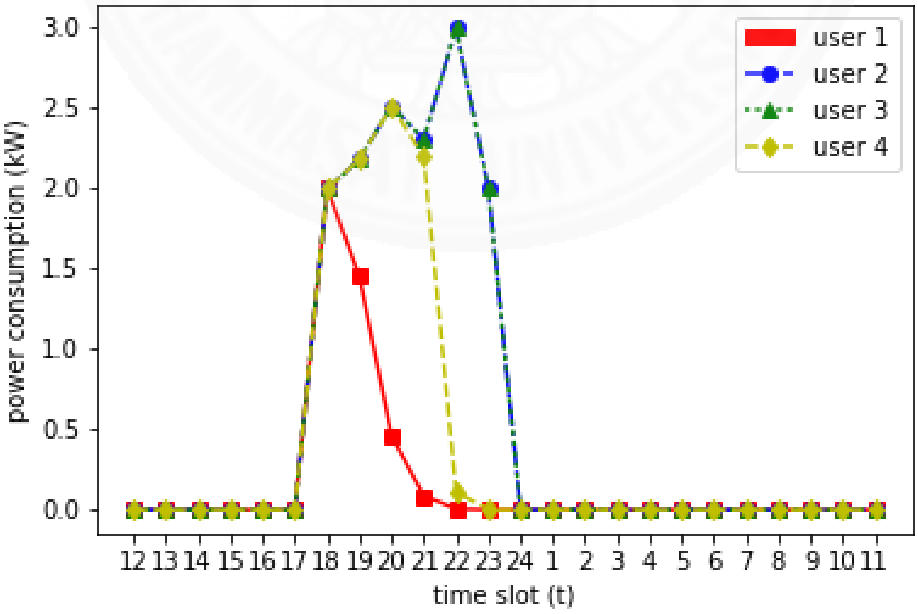


Figure 4.2: Actual Power consumption per user, APS scheduling

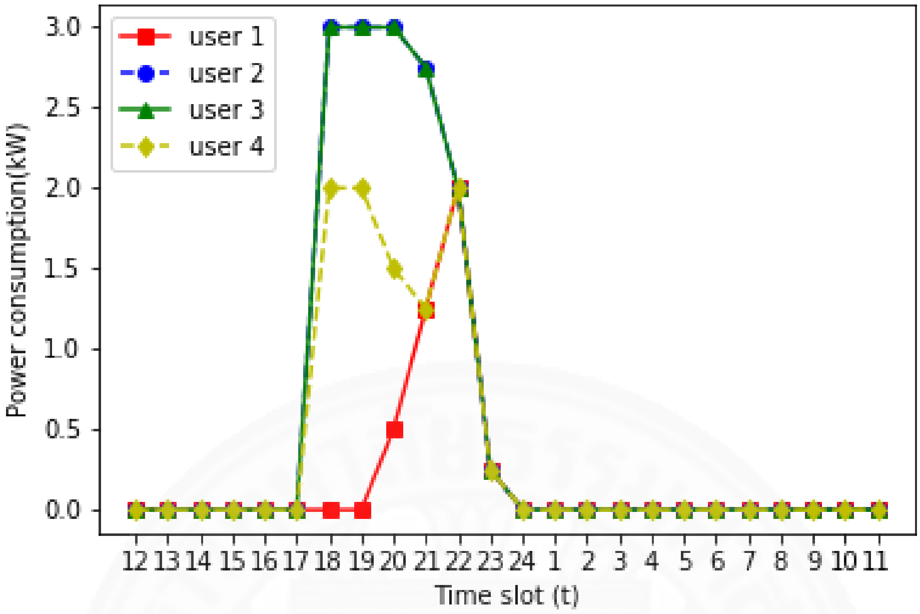


Figure 4.3: Actual Power consumption per user, WF scheduling

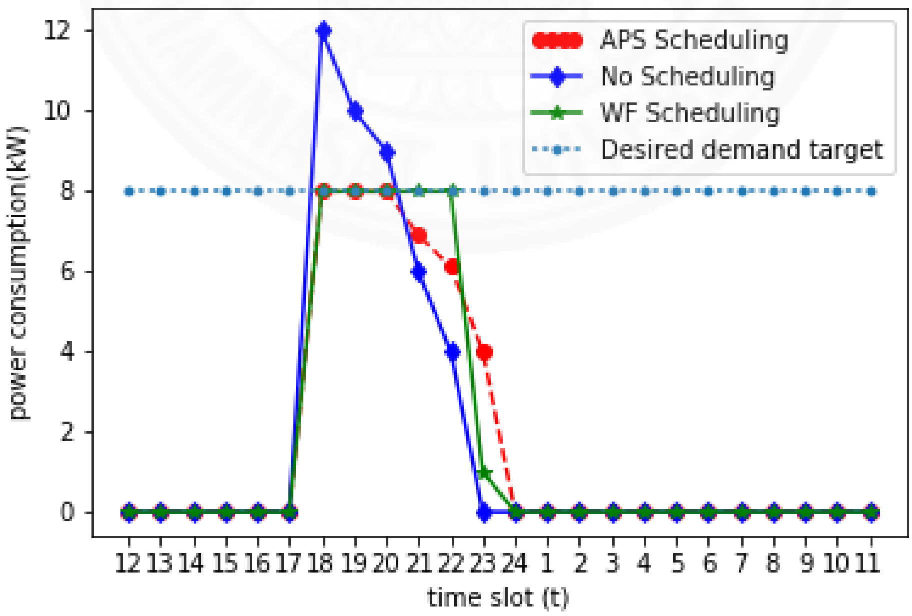


Figure 4.4: Aggregate Power consumption, no scheduling, APS and WF scheduling

In Fig. 4.4 the total power curves for all the 4 households is shown. The WF can keep the aggregate power consumption at desired level until 23:00 where all all EVs are almost full. On the contrary, APS tries to be fair by charging each EV at the same factor of requested power, r^t, as shown in Fig. 4.2

4.2 Twenty households with EV and Base Load

In this section we consider a residential area having 20 users, which collectively has load profile similar to an area in Pattaya where PEA is planning to have the Smart Grid project. PEA has 4 Distribution transformer sizes and the base load for each is displayed in Fig. 4.5. For our scenario a 50 kVA transformer is used. The maximum usable power, Z^t is about 40 kW,[1] so the available target power for scheduling of EVs is $40 - C^t$, where C^t is the baseload demand for time slot t. The EV considered for has a minimum charge of 0 kWh and maximum charge of 3.5 kWh.

In Fig. 4.6 all the EVs had the same arrival time of 18:00, departure time of 7:00 and as well as same initial SOC of 15% (3.6 kWh). Without any scheduling involved, the peak is at about 70 kWh with the profile being violated from 18:00 until 23:00 as all EVs are plugged in and being charged with 3.5 kWh, they all begin charging immediately they are plugged in. As expected every EV has the same priority of requirement thus they are all treated equally and that is why both the APS and WF have the same curve.

On the contrary in Fig. 4.7 we have EVs which have the same initial SOC of 15% (3.6 kWh), same departure time of 7:00 and different arrival times of between 18:00 and 20:00 which were independently, identically distributed uniformly. It can be observed that from 19:00 to midnight the desired demand target is violated under no scheduling. APS and WF makes sure that this violation does not happen. We can see a change between APS and WF from 03:00 as some EVs become fully charged and stop requesting for a full charge power of 3.5 kWh. Nonetheless, both APS and WF ensures full charge of EVs by departure time.

[1]This 40 kW target aggregate is used for illustration only for 80% utilization factor so as to account for transmission loss and transformer ineffeciency. In practise, PEA only allows 40% utilization factor, which means 20 kW, but this detail is not significant for our purpose.

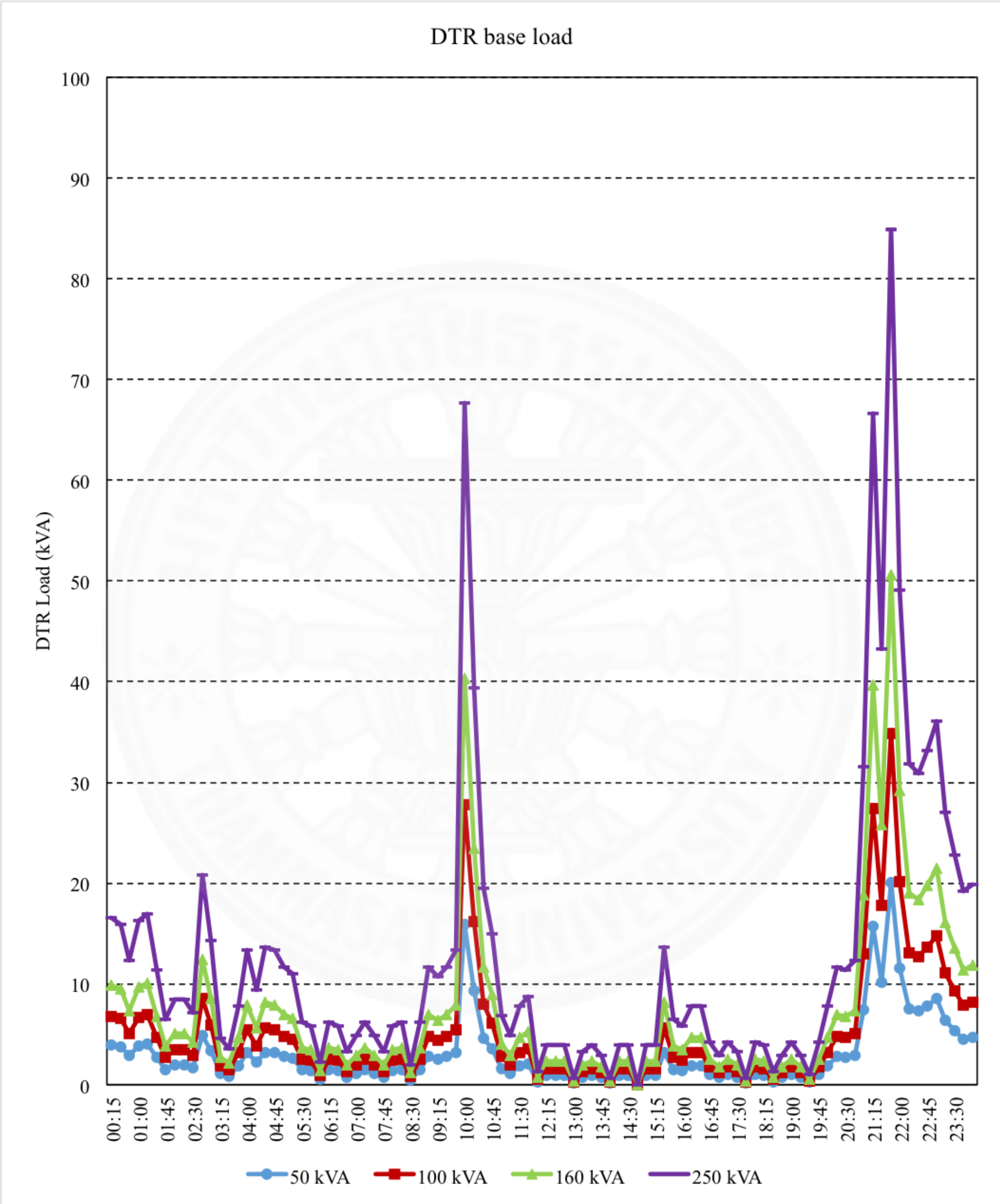


Figure 4.5: Base load profile of Pattaya Central Area 2 [3].

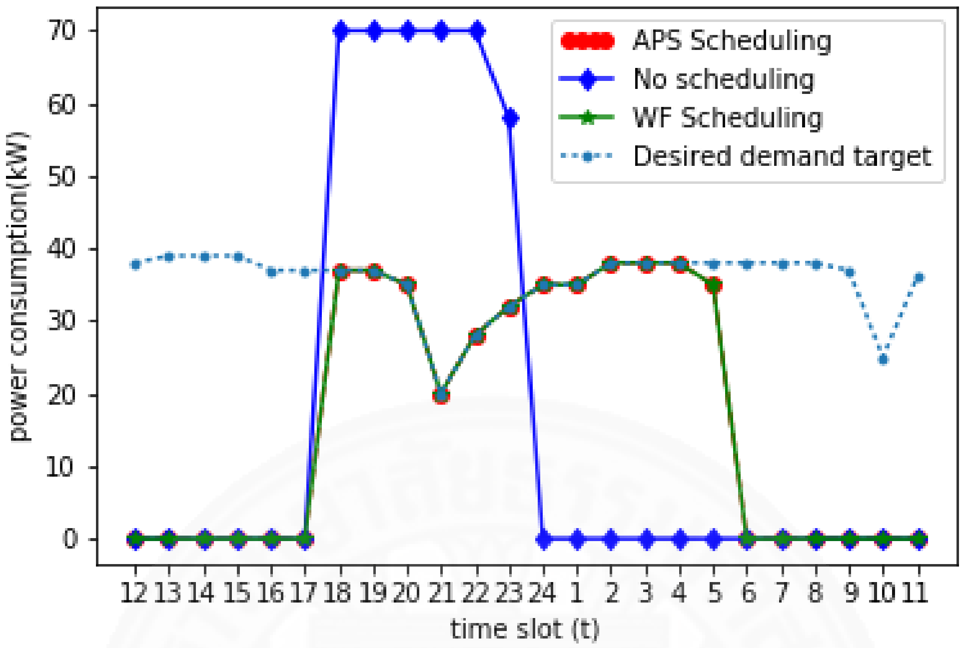


Figure 4.6: Target load profile and aggregate power consumptions under no scheduling, APS, and WF, under same arrival times and same initial SOC.

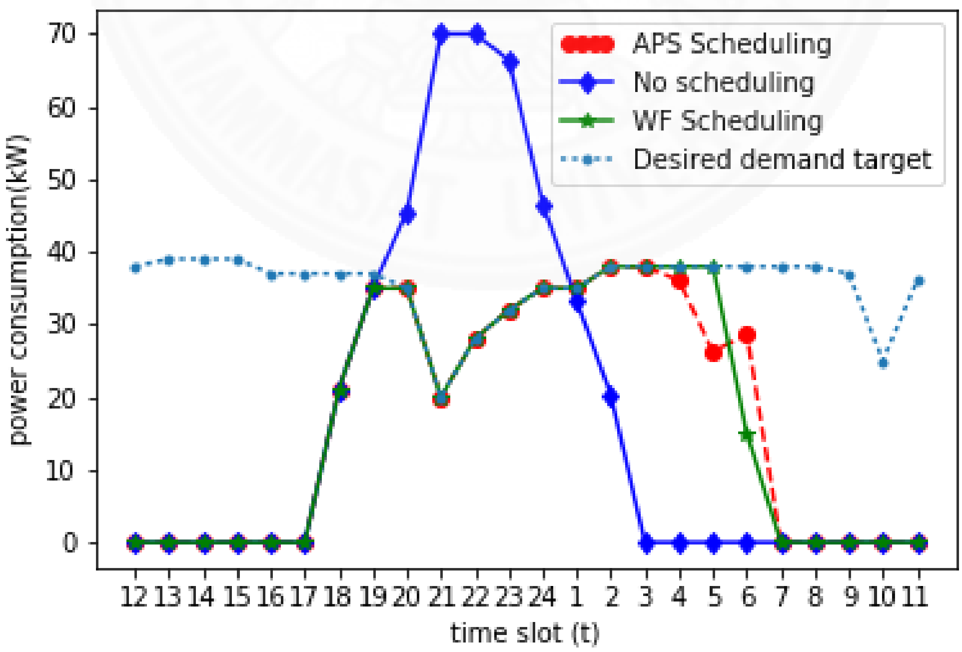


Figure 4.7: Target load profile and aggregate power consumptions under no scheduling, APS, and WF, under random arrival times but same initial SOC.

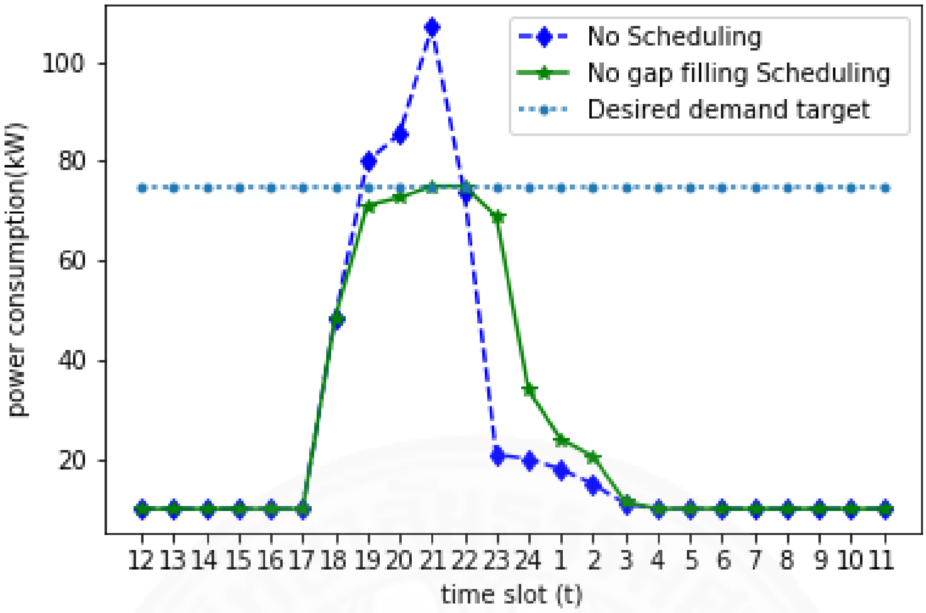


Figure 4.8: Power consumption, each user has an EV, no scheduling and with scheduling, no gap filling, aggregate Z^t = 75 kW

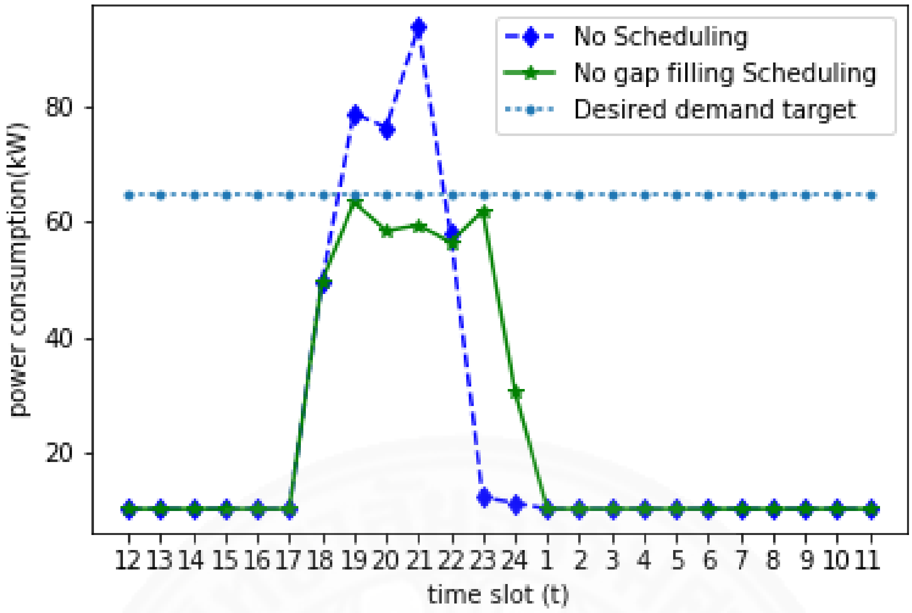
4.3 Gap Filling

For illustration, we consider an area with 10 users each having 8 devices. We use a 24 hour time period (12 noon - 12 noon the following day) assuming that a timeslot lasts an hour. We shall compare scheduling with with no Gap Filling, with Gap Filling 1 and with Gap Filling 2. Thereafter we shall compare the deviation of each Gap filling. Python and pyomo language was used to simulate our code and we solved solved our optimization problem using CPLEX solver.

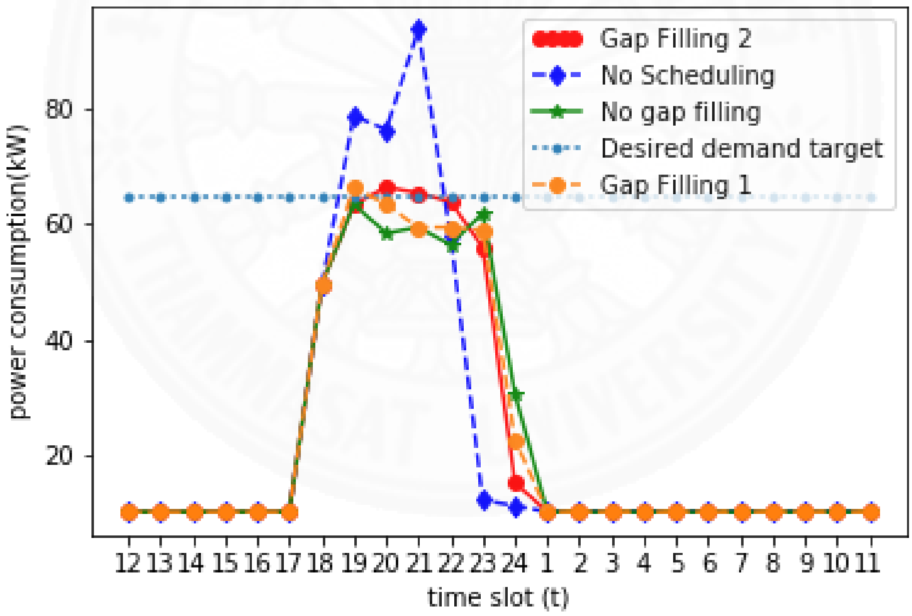
In Fig. 4.8 we observe the power consumption of the whole area when each user has 7 appliances of type 1 and type 2 appliances and an EV (type 3 appliance) which charges with flexible power range between 0 kW to 3 kW. Without any scheduling the power usage can go upto 110 kW and with the introduction of scheduling and desired power aggregate of 75 kW, the power usage is kept as close to the target as possible and this is due to EV which has the ability to charge at different rates. As a result there is little to no gap to fill in most timeslots around the peak hours when EV load is present.

In Fig. 4.9a where we consider each user to have 8 appliances which are either type 1 or type 2 appliance which consume constant power at each operation timeslot. This is so we can observe the gap that is present when there is no EV load. The gap where more power can be utilized is between around 19:00 and 23:00.

In Fig. 4.9b we applied Gap Filling 1 and Gap Filling 2, respectively to the scheduling. For Gap Filling 1 we chose the best case scenario. We can observe that our proposed method (Gap Filling 2) fills the gap in a better way than Gap Filling 1.



(a) Power consumption, no scheduling and with scheduling, no gap filling



(b) Scheduling with Gap filling 1 and Gap filling 2

Figure 4.9: Power consumption, Desired Demand target, Z^t = 65 kW

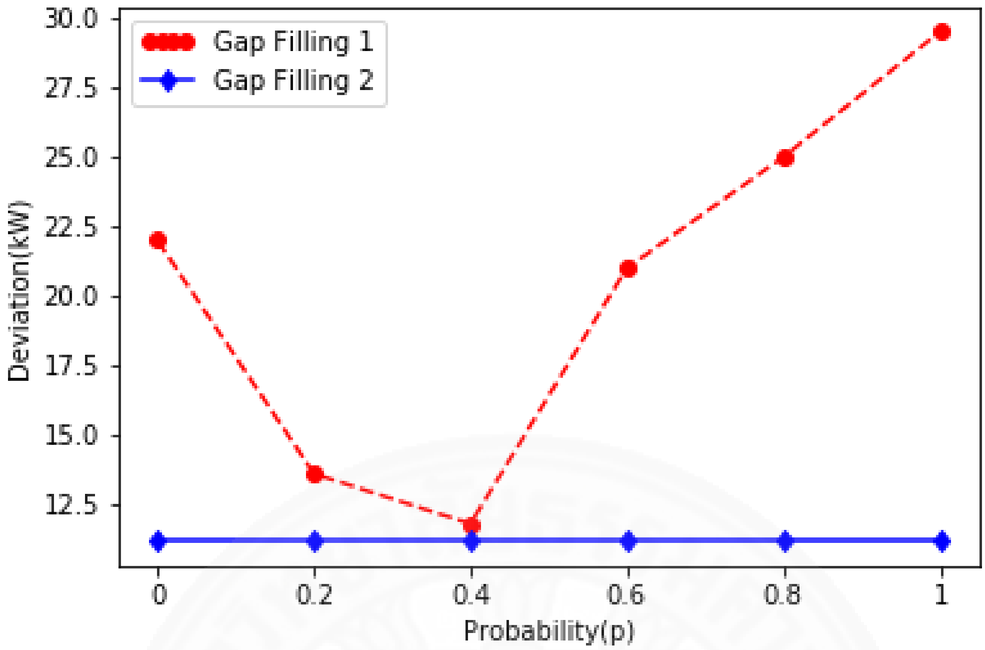


Figure 4.10: Deviation of Gap Filling 1 and Gap Filling 2

In order to see how Gap Filling 2 fares with Gap Filling 1 for various probability p, we define the deviation of the aggregate power consumption from the target aggregate as

$$\text{Dev} := \sum_{t=1}^{T} |Z^t - A^t| \cdot I_{[C^t + F^t > Z^t]} \tag{4.1}$$

where the function

$$I_{[B]} := \begin{cases} 1, & \text{if event B is true} \\ 0, & \text{otherwise} \end{cases} \tag{4.2}$$

Recall that Z^t is the desired total demand target of the area at timeslot t, A^t is the actual used power at timeslot t, C^t is the total amount of requested fixed load of the area at timeslot t, and F^t is the total amount of requested flexible load of the area at timeslot t.

Fig. 4.10 shows the plot of deviation for the two version of gap filling methods at various probability p. Note that Gap Filling 2 is independent of probability p which is one the advantages of using Gap Filling 2 as there is no need to set an appropriate p. For Gap Filling 1 in this particular example, the optimal probability is at p around 0.4. Note that while the optimal probability p will vary depending on real scenarios, our proposed Gap Filling 2 does not require any tuning of this probability and hence more robust.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

Scheduling of EVs can be a good and effective way to reduce demand peaks and as well as keep the power consumption in residential areas below the target demand to avoid over loading or damaging the distribution transformers. In this thesis we studied how APS can be used in order to charge EVs in a residential area where each house has an EMC and is able to communicate with its neighbors about their total fixed and flexible load. This is done in order to help an EMC computes how much power it is allocated in order to schedule its smart home appliances including EV.

A mixed integer problem was formulated and used to schedule the appliances, this problem was simulated using python and *pyomo* package and solved by the *CPLEX* solver. A WF algorithm approach was also implemented for the same scenarios for comparison with the APS. APS was found to be fairer than WF as EVs were allocated power by the same ratio regardless of their SOC.

A new Gap Filling algorithm was also proposed in order to keep the actual used power as close to the Target demand as possible and allow appliances to finish their operation earlier. This Gap Filling algorithm is done by each EMC after optimization whenever there is gap to fill.

5.2 Recommendations

Though some different scenarios were implemented and analyzed in this thesis, there are still some interesting works left as future research:

- Appliances that have different ways of consuming power depending on other external influences such as outside temperature and occupancy should be considered, e.g air conditioners.
- Incorporation of other energy sources should be considered so as to charge storage batteries during the day in order to use during peak hours especially in the evening.
- Higher penetration of EVs should also be studied.
- Different departure times should be considered, and EVs which leave earlier should have an opportunity to be prioritized.
- Stochastic optimization can be used to consider uncertainities in EV parameters and base load.

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