A DEMAND RESPONSE MODEL AND ITS APPLICATION TO PHEV CHARGING

A Project Report

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by

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CERTIFICATE

This is to certify that the thesis entitled **"A DEMAND RESPONSE MODEL AND ITS APPLICATION TO PHEV CHARGING"** submitted by **Rahul Kumar Meena, (EE12B103)** to the **Indian Institute of Technology Madras** in partial fulfilment of the requirements for the award of the degree in **Bachelor of Technology and Master of Technology** in **Electrical Engineering** is a bona-fide record of the project work done by him under my supervision.

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Rahul Kumar Meena

ABSTRACT

Electric Vehicles are the future of transportation as they are not only economical but also help the environment by reducing the GHG emissions. But, this significant rise in the number of PHEVs will cause a huge demand in electricity which would be impossible to meet with the existing infrastructure in place. This calls for measures to meet maximum demand with minimum possible increase in infrastructure; one way to do this is to use dynamic pricing and bring the Peak Average Ratio as close to 1 as possible. We need well devised Demand Response technique to pull the demand from peak hours to off peak hours. This project studies an algorithm which uses the consumers' willingness to pay (WTP) parameter to provide differential Quality of Services (QoS) to the consumers. Through this dynamic pricing method users can adapt their demand and willingness to pay accordingly to maximize their utility while meeting their individual demands. Simulations are run to test the dynamicity and convergence of the algorithm. Then the algorithm is applied to PHEV Charging in smart grids where each user can adjust their rate of charging according to their preferences. We then check the practicality of the algorithm by running the simulations for different values of involved parameters such as initial WTPs, number of PHEVs connected to the grid etc.

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CHAPTER 1

INTRODUCTION

With the growing population, the number of private transportation vehicles is increasing very rapidly. Excessive number of these vehicles is causing enormous damage to the environment through the release of GHGs which contribute to the global warming effect. Amidst this, Plug-in Hybrid Electric Vehicles have emerged as favourites to replace the traditional fuelled vehicles. However, this sudden rise in PHEVs has created another problem: Various users would return from their work offices at similar times and immediately plug-in their PHEVs for charging. Such behaviour would cause a very high peak demand in the electricity and the grid will fail to meet these demands. A study suggested that if there is a 30% PHEV penetration in the US market, the load associated with the PHEV charging on the grid would be around 140 Giga Watts which alone is around 18% of the total US summer peak electricity load.

One way of solving this kind of a problem would be to expand the available electricity infrastructure and ensure that it is capable of meeting the peak demand that it will be exposed to, but the huge prices involved in the expansion of the infrastructure and the lack of available resources renders this option infeasible.

Another way is to implement a proper demand response mechanism which will encourage users to adapt their demands such that the load is shifted from peak hours to off-peak hours. This shifting will enable the grid to manage the electricity demand more aptly because now the peak demand would be within its limits. This kind of a demand response execution requires some sort of incentive for the consumers to not participate in the program and adapt their electricity requirement to make the overall demand as steady as possible.

Usually, dynamic pricing is the best measure to achieve this; the electricity companies would make electricity expensive during the peak load hours and cheaper during hours when the demand is lower. Electricity companies usually have a very good idea of the load pattern that is going to be followed any given day and coordinating this data along with the supply capacity of their generation plants they can devise a more dynamic form of their electricity pricing. The closer the demand pattern to the pricing pattern, the better the load management and a more steady overall demand from the consumers.

Some of the classic forms of load pattern management are Peak Clipping, Load Shifting and Valley Filling.

- Peak Clipping solely focuses on reducing the peak electricity demand, it doesn't care about the rest of the demand curve but only tries to bring the peak value into its achievable value.

- Valley Filling is when the depression in the demand curve are filled so as to reduce the possible demand later, this can be done by lowering the pricing when the demand is low or by encouraging users to store energy backup so they can be utilised at the peak hours.

- Load Shifting is when the loads are shifted from peak to valley times, this includes applications such as space heating, water heating etc. The difference between this and clipping is that here the net demand is not changed whereas in Clipping the demand is eliminated.

These forms are explained by the following diagram:

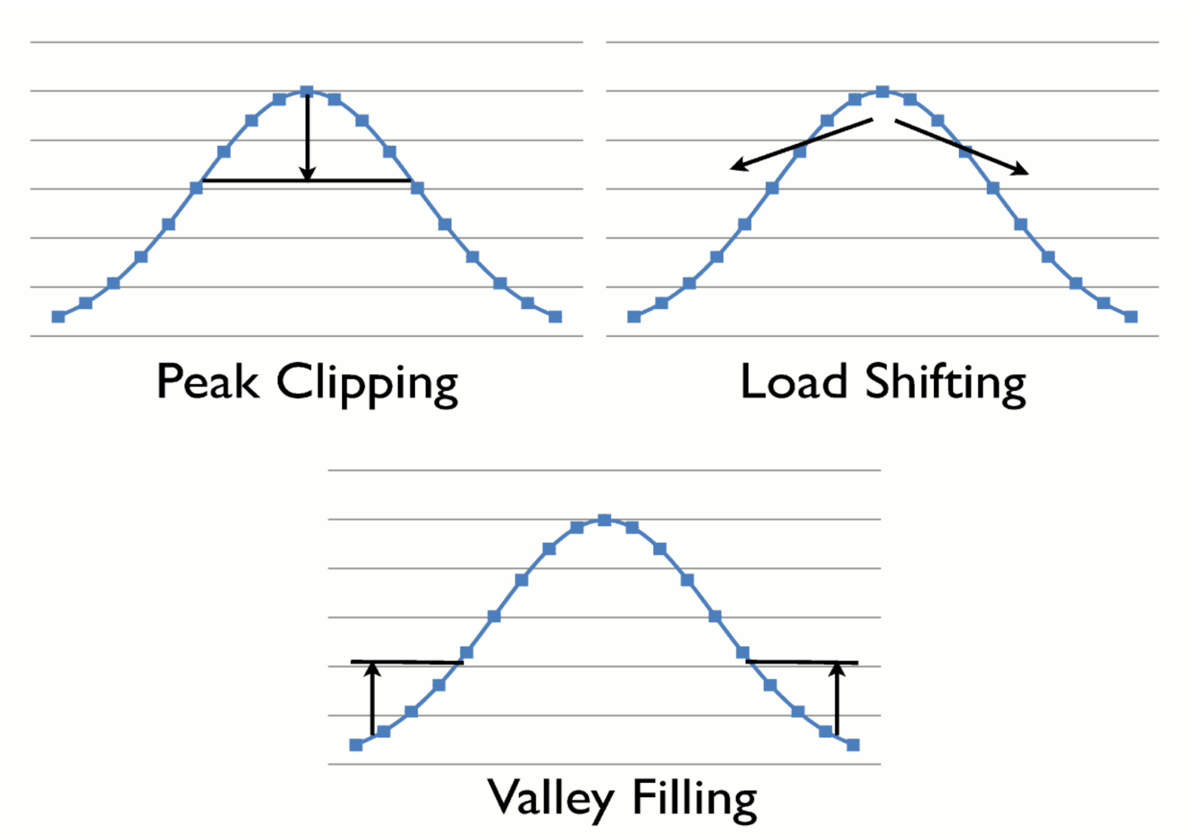


Fig 1.1: Classic forms of Load Pattern Management

1.2. DR USING LOAD SCHEDULING

There is a huge research going on recently on the Demand Response techniques facilitated by Smart Grids using load scheduling. Different approaches have been taken to incentivize a consumer to curtail specific loads to reduce the demand in peak hours. In this subsection, we take a look at some of the techniques suggested to formulate a demand response algorithm.

1.2.1 WHEN THE USER DEMAND IS KNOWN BEFOREHAND

When the electricity company already knows the consumption pattern of the end-user, it can ask the user to submit a list of all the appliances in the order of priority of usage for the user. This preference list is then matched with the level of usage of that appliance and used to curtail the least prior load when the demand exceeds the supply. Depending on the priority each appliance is associated with a level of comfort or discomfort and when the supplier 'cuts off' any appliance, the user is compensated based on the level of discomfort that he has to bear due to the cut off. An optimization problem can be formulated around the parameters of supply price, discomfort level and the production constraints to practice the demand scheduling.

In some other cases, the formulation is more autonomous and the incentive to curtail a load is communicated from the supply end based on the demand-supply mismatch. Here it is completely up to the end user whether he wants to turn the load off or not. Suppose users don't curtail enough load to cancel out the demand-supply mismatch then the incentive is further increased. These formulations are enhanced by game theory based optimizations and require a bi-directional communication line to be implemented properly.

In each of these techniques the supplier has to know the expected demand pattern to evaluate the amount of incentive to pan out to the customers. Also, the time scale is divided into a number of slots and the scheduling is done in numerical iterations. Consumers often have back-up generators or other electricity storage devices which they may charge during the cheaper hours and then turn these back-ups on and curtail their load supply in agreement with the supplier in return for a special incentive.

Several ideas from topics such as distributed computing and game theory are incorporated in application of these formulations.

The implementation of such a system requires that all the households connected to power line are also connected to communication devices such as ECS (Emergency communication system) with each other so that the contributions made on the demand side accounts for all the users involved are communicated throughout the system and the system is truly autonomous.

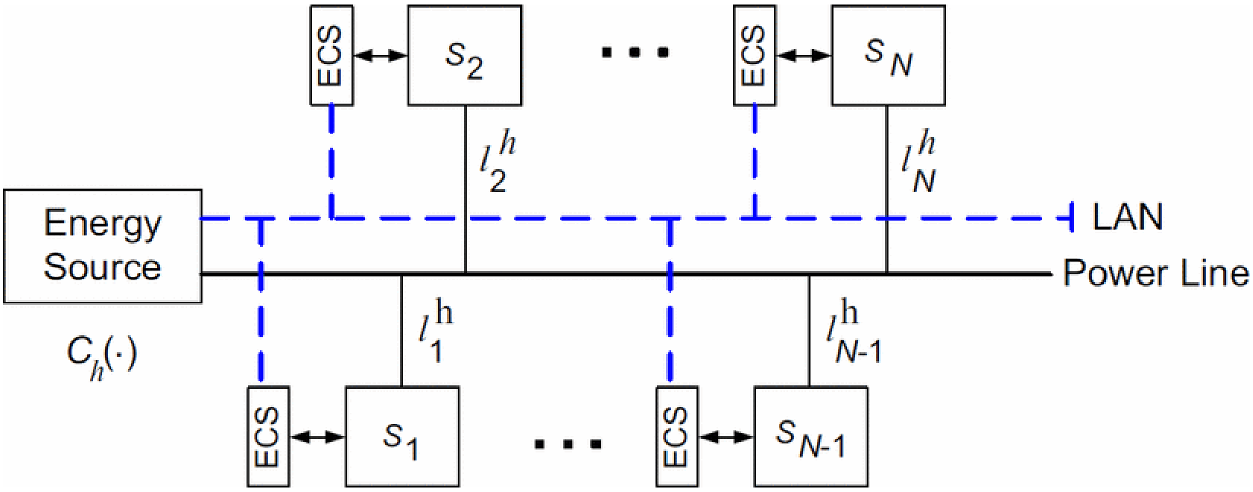


Fig 1.2: A sample Smart Grid system for DR with N participants

1.2.2 PRACTICAL IMPLEMENTATION CONSIDERATIONS

The implementation of any kind of Demand Response requires that the end user is represented by an automated entity fitted with a smart device programmed to manage the energy ins and outs by itself. Let's call this entity Energy Management System (EMS). There is a Home Area Network which connects to all of these appliances at home via the EMS, typically powered with wireless networks.

Based on the pricing information it receives the EMS calculates the demand in the next time slot and communicates it to the supplier through the HAN. Based on this demand, the supplier can immediately calculate the price for the next time slot and hence the system works on numerical iterations.

The basic EMS unit consists of a smart electronic device and a communication module for example ZigBee.

- The smart electronic device is used to collect the electricity consumption data from all the users and allows the end users to review the power consumption vs. the pricing.
- The communication module also facilitates the data transfer between the EMS and the load controllers.

Some researchers suggested that the appliances can be divided into two categories, hard and soft appliances based on the nature of their usages. Hard appliances are those whose energy consumption should not be curtailed such as the refrigerator or heater which require constant usage. Soft appliances on the other hand are those whose demands can be shifted to other time slots without much inconvenience as long as the job gets done later, examples of these appliances are washing machine, PHEV charging etc.

When EMS unit has to curtail a load it would look up to the hard appliances by default and try to reduce demand by switching off minimum number of hard appliances. If the demand is still not met then the soft appliances are switched off. The compensation provided to the consumer for curtailing soft load would be more than the hard load.

1.2.3 ROLE OF PHEVs IN DEMAND RESPONSE

Plug-in Hybrid Electric vehicles have a prevalent role to play in the Demand Response in the future because of the versatility in their charging patterns and their sheer market penetration here we discuss a few points which make PHEVs’ role in demand response so important.

Flexible charging rates

PHEV Charging is very flexible, not only can the demand be shifted across the time slots it can also be adjusted at a varied rate. The Electric Power Researched Institute has proposed three different levels of PHEV charging. These levels can be switched depending on the demand-supply of electricity in any given time slot. In Level 1, charging is done through 120VAC 15A outlets which are rated at 1.44kW. These would be the most common charging method. In Level 2, 240VAC 40A outlets can be provided. Whereas, in Level 3 at a very high market penetration of PHEVs a 480VAC 100A outlet can be provided, these outlets would be limited to fast-charging stations only.

Impact on renewable energy integration

PHEVs allow the possibility to integrate Renewable Energy Sources into the traditional electricity by acting as a backup when there is a shortage in the available renewable energy. This is known as intermittency effect. One of the main obstacles identified in the integration of the renewable energy has been identified by the researchers as the lack of storage energy, a huge potential lies in the market PHEV penetration to tackle this problem provided the market has appropriate DR programs in place and the V2G technology continues to develop. This will allow the users to turn to the PHEV stored energy when there is a shortage in the renewable energy supply.

Table 1.1: Some popular PHEVs and their battery data.

PHEV Model	**Battery Type**	**Capacity(min.)**	**Range**	**Charging Time**
Chevy Volt	Lithium Ion	16 kWh	40 miles	6.25 hours
Nissan Leaf	Lithium Ion	24 kWh	73 miles	7.50 hours
Mitsubishi Outlander	Lithium Ion	13 kWh	33 miles	5.00 hours

Potential cost savings

As PHEVs become more exploited for their demand response ability, the social welfare will be maximized as both utilities and end-users save money together. Not only does the usage of electricity is cheaper than the cost of gasoline, by participating in real time pricing programs the consumers will have more potential of cost savings. Soon, the consumers will be able to make easy savings by making simple changes to their daily routine and adjust their electricity usage pattern. Electricity supplier would also make benefits by decreasing or delaying the production when the transmission capacity is reached. With the development of V2G technology it will soon be very simple to balance out the load to generation, given that sufficient number of PHEVs are participating the Demand Response program.

1.3. OVERVIEW OF THE PROJECT

In this section, we take a look at how the following chapters are organised.

Chapter 2 explains how we go about formulating the Demand Response problem. We discuss the various parameters involved and the significance of those parameters. The various terminologies used are explained, several variables are defined and the constraints on the system are discussed along with the validity of this formulation and the assumptions made.

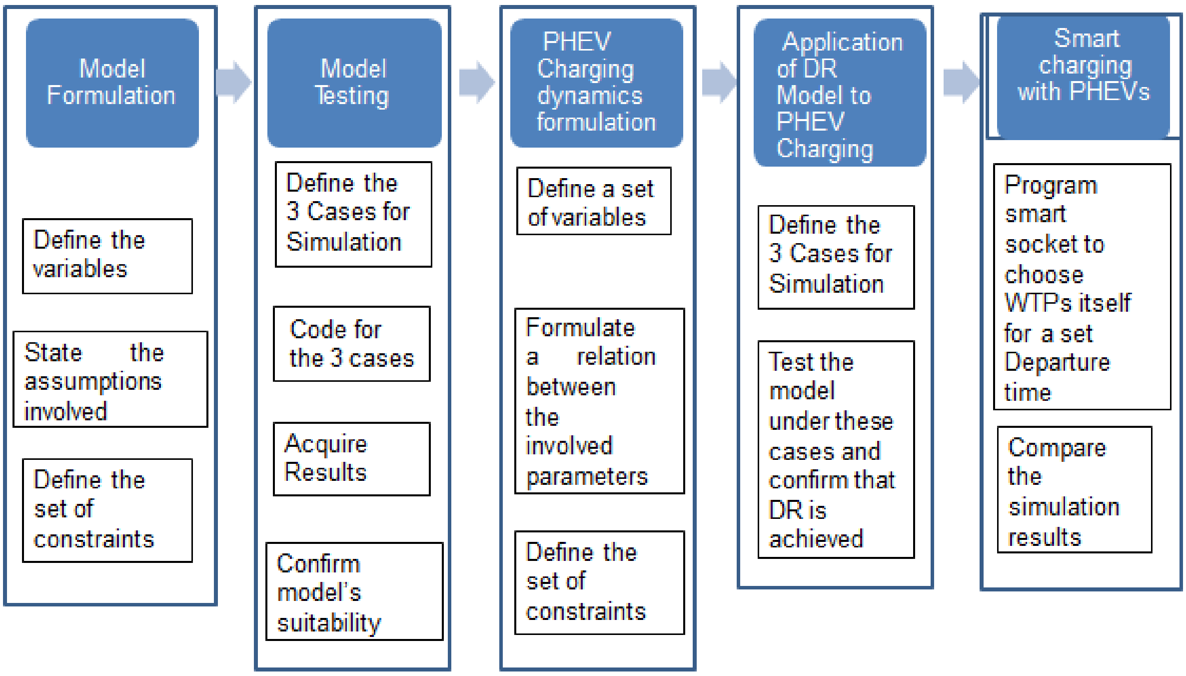
Chapter 3 discusses the idea which we used in designing the said formulation, namely the congestion pricing. We also discuss the proportional fair pricing method which is the key to our algorithm. The simulation parameters and their practicality are explained along with possible improvements in the formulation.

Chapter 4 discusses the suitability of our formulation in various scenarios to test its practicality. We test the MATLAB simulations for various values of the parameters involved and discuss their significance. We check if our algorithm converges for these values.

In chapter 5, we see how our algorithm relates to actual PHEV Charging scenario formulate the problem in terms of state of chare, battery efficiency etc. and see how it fits and then we conclude the study along with a brief discussion of the possible future developments on the issue.

1.4. SUMMARY

This work has been summarised in the chart below:



CHAPTER 2

FORMULATING THE ALGORITHM

The purpose of this chapter is to formulate our model in which the only information available to the end-user is the current price and the users adjust their usage rates based on the set willingness to pay and hence they get what they pay for. The prices are updated constantly and the consumers too have to keep their usage rates in check based on their WTP.

2.1. PROPOSED DEMAND RESPONSE MODEL

We first start the formulation by defining the variables that will be used in the simulation.

- Time is divided into discrete slots and each time slot is represented by *n* such that n = {1, 2, 3, 4…}.
  - $v(n)$ represents the value of parameter v in the n^{th} time slot.

- Let the variables for each time slot be defined as:
  - $x_i(n)$: the demand supplied to the user i from the grid in the time slot n.
  - p(n) : the unit price of electricity in the time slot n, this price is a function of the aggregate demand and the market capacity.
  - $w_i(n)$: the willingness to pay of the end user in the time slot n. This parameter can be adjusted based on the price set by the supplier.
  - γ_i : the convergence parameter of the end user, this indicates how fast the user adjusts their demand based on the market price incurred and willingness to pay mismatch.

- We propose that based on the current prices and user's WTP, they adjust their demands:
  - $x(n+1) = x(n) + \gamma\,(w(n) - f(n))$, where
  - $x(n+1)$ is the rate of electricity supplied to the user in the n+1 time slot
  - $w(n)$ is the willingness to pay indicated by the user.

- $f(n)$ is the feedback price signal received by the user, it is equal to $x(n)p(n)$

2.2 ASSUMPTIONS WITH THE MODEL

- We assume that the market follows an iso-elastic pricing function. This means that the market price is a function of the market capacity and the overall current demand:

$$\boldsymbol{p(n) = a*(x/C)^k},$$

  where, a and k are constants, x is overall demand and C is the market capacity.

- We assume that the demand x is a continuous variable, which may not be the case in reality.

- The waiting time associated with load rescheduling is considered as zero and we assume that this delay doesn't lead to any changes in the supply-demand balance.

- The battery efficiency is assumed to be constant throughout the operation, the system is assumed to be lossless and the overall market demand is simply the sum of all individual demands.

2.3 PRICING MODEL & ADAPTION OF USAGE RATES

Now that we have explained all the assumptions and the variables involved with our algorithm let us take a look at the pricing model so we can proceed with the simulations.

Our model follows the simple congestion pricing model which means that the users pay more when the resources are more congested. But in an open electricity market the utility should also be able to meet all the demand incurred by the end users, to ensure this the electricity rates are communicated to the end users and based on their willingness to pay they can adapt their usage rates. This adjustment is done based on the difference between the willingness to pay and the 'feedback' signals i.e. the current price incurred by the user. Since each user has a different sensitivity towards the price we also incorporate the convergence parameter γ for each user. This is evident from the expression:

$$x(n+1) = x(n) + \gamma\,(w(n) - f(n)) \qquad (2.1)$$

as,

(i) $w(n) > f(n)$:

when the willingness to pay exceeds the price currently being incurred the consumer will increase his consumption rate in the next time slot.

(ii) $w(n) < f(n)$:

when the willingness to pay is less than the price currently being incurred the consumer will decrease his consumption rate in the next time slot.

(iii) $w(n) = f(n)$:

when there is a match between the willingness to pay and the price being currently paid, the user will maintain his consumption rate in the next time slot.

In this model, each user i influences the consumption rates of the other users because the feedback mark $f(n) = x(n)\,p(n)$ and $x(n)$ & $p(n)$ both are dependent on the consumption of each and every user.

PHEV parameters

We now turn our attention to the application of the above proposed pricing model to a PHEV Charing scenario. All the PHEVs are attached to a smart socket which controls the WTP of each user and communicates it to the supplier. Based on this WTP data received from all the PHEVs the supplier controls the rate the charging of each PHEV based on the above formulation, when a PHEV is charged completely it is removed from the charging pool.

To formulate this, we introduce a parameter called State of charge (soc) which ranges from [0,1] depending on the charging level of a PHEV, 0 when the battery is completely discharged and 1when it is full. The soc equation can be modelled as follows:

$$y(n+1) = y(n) + (\alpha/B) * x(n) \tag{2.2}$$

here, α is the battery charging efficiency, B is the Battery Capacity and $y(n)$ is the battery *soc* in a time slot n. It can be seen from the equation that when the charging rate $x(n)$ is high, $y(n)$ will reach 1 in less time i.e. the battery charging will finish quicker.

2.4 CONSTRAINTS

There are several parameters involved in our model and also several constraints associated with these parameters. While performing simulations it is important that we take care that none of these parameters cross their constrained value. These constraints are explained below:

$x(n) >= 0;$ negative demand has not been incorporated in our model
$w(n) >= 0;$
$\gamma(n) > 0;$
$p(n) > 0;$ market parameters a, C and k are positive so spot price is positive.
$0 < \alpha(n) < 1;$ Charging efficiency is set between 0 to 100%.
$B > 0;$ Battery capacity is positive.
$0 < y(n) < 1$; Battery state of charge is always between 0 to 100%.
$k > 1$; in an iso elastic market

CHAPTER 3

METHODOLOGY

The goal of our project is to propose a demand response algorithm which will help in spreading out the PHEV charging load over the time period. To do this, we have proposed a DR algorithm which provides differential Quality of Service to different users based on their willingness to pay. The only information available to the end users is the current market price. In the following section, we divided our work in two parts.

In the first part we check the suitability of our DR algorithm by checking its convergence and responsiveness for various ranges of practical parameters. We do this by simulations in MATLAB and studying the obtained plots. In this first series of simulations, we test the proposed DR algorithm for its robustness for various practical scenarios. We do this by simulating three different test cases: In the first case we run a basic case where all users start with a same initial demand but all have different WTPs, we see how this leads to a differential QoS and how the prices settle to equilibrium in some time. In the second case, we consider a scenario where users with lower WTPs have a high initial demand, we check that once we implement the algorithm the demands quickly crosses over to a new equilibrium which reflects each user's WTP. In the third case , we see what happens to the system if all the users suddenly change their WTPs to an arbitrary value, we use the *rand* function in MATLAB to generate random WTPs and see the system convergence for the same.

Once we have finished the first series of simulations we have established that the proposed DR algorithm if implemented correctly, would not cause any disruptions in the system and would indeed help us in achieving the goal of DR in a stable way for all practical scenarios.

In the second series of simulations, we then see how we can enforce this proposed algorithm to the actual PHEV charging application. Firstly we establish that all the PHEVs are connected to smart sockets which allows the supplier to control the charging rates of the PHEVs based on their users' WTPs.

After this, we will program the smart socket to make decisions on its own and be able adjust WTPs by itself such that the charging is done by the time of departure, this is done based on iterations such that the user always pays close to the lowest possible amount as he selects WTP just that his average charging demand rate is just met. A detailed study on this could be done with the incorporation of topic such as statistical analysis, machine learning, data mining etc.

We introduce the concept of State of Charge (soc) to incorporate in our algorithm to ensure that the PHEVs that have completed their charging are disconnected from the market dynamics. In the second part of simulations, we see how the overall electricity demand pattern changes over time when the DR algorithm is implemented. We see that in a huge market with a large number of DR participants the valley filling goal is achieved very concisely.

We use MATLAB to perform all the simulations involved, the problems are solved through rapid code iteration and the results are stored in two dimensional arrays as data plotted against the recorded time slot. Random numbers where needed are obtained through the *rand* function and multiple simulation results are cross checked to ensure that the simulations are suitable in any random set of parameter values.

CHAPTER 4

MODELING AND SIMULATION

We use this chapter to run simulations on our proposed DR model and check its suitability and understand its concept for practical market scenarios. **Please note** that since in this section the only purpose is to check the stability and behaviour of the proposed model, the units of the parameters involved don't matter and we have omitted them, they are however included in the practical charging scenarios in the next section.

We take three special cases to test this:

Case 1: All the users start with the same initial demands but have different WTPs we study their behaviour in our algorithm and also see how it affects the overall market price.

Case 2: All users start out with completely different initial demands and have contrasting WTPs; we see how their usage rates come to an equilibrium value which concurs with their WTPs.

Case 3: In this scenario, users start out with different WTPs and then after time slot 100, we randomize the WTP parameters by adding a random number from [-5,5] to each of the WTPs, we see if the usage pattern converges back to an equilibrium again.

4.1. DATA USED FOR SIMULATION

We divide the time period into discrete time slots, the simulations are run through rapid iterations and the values of the involved parameters are calculated in each time slot and stored in a 2D array.

We perform our simulations in an iso-elastic price market, which means that the spot price is given by:

$$p(n) = a*(X/C)^k, \qquad (4.1)$$

as explained in chapter 2.

Throughout this series of simulations we assume that the value of the involved constants and parameters are as follows:

a = 1;

k = 4;

and C = 100 (market capacity).

In this chapter we assume that there are N = 10 users participating in the market.

4.2. MODEL TESTING AND SIMULATIONS

Case 1:

This is a basic simulation to understand the dynamic of our algorithm, we assume that all users start with a starting initial demand of 2 units and have WTPs range from 11 (for User 1) to 20 (for User 10). Convergence parameter γ = 0.20 for all users. When we apply our DR algorithm users quickly adapt their rates as:

$$x(n+1) = x(n) + \gamma\,(w(n) - x(n) * p(n))$$

and after a short transient period, each user settles to a stable value determined by their WTPs.

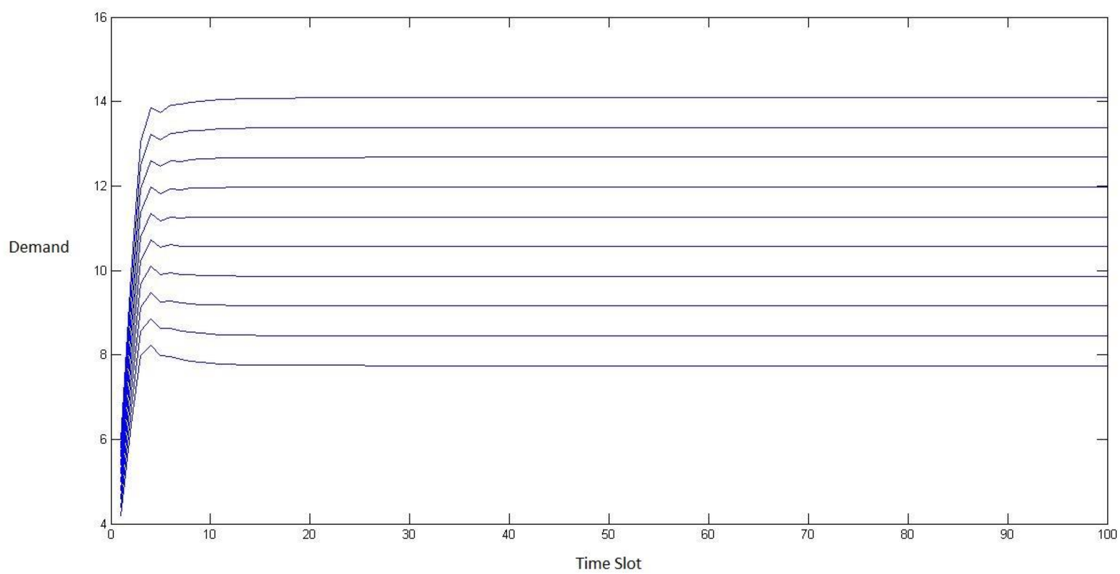


Fig 4.1: Users converge to a stable value based on WTPs

All the users settling to stable value also brings a stable market price as other parameters remain constant along with overall demand. As seen from the MATLAB simulation below, the market price *converges to 1.42 units*.

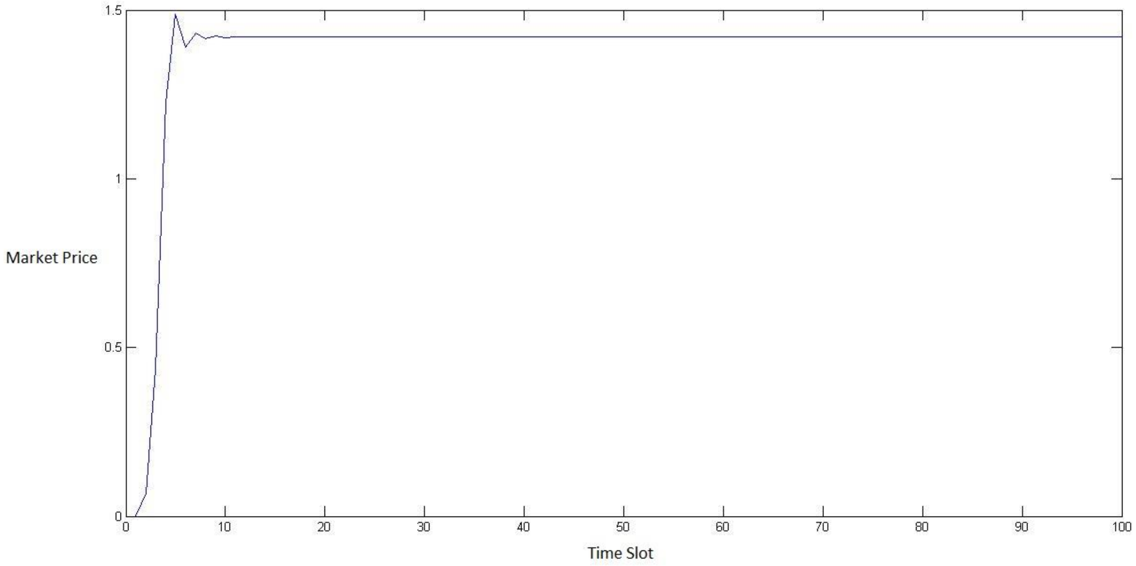


Fig 4.2: Market price equilibrium at 1.42 units

Case 2: In this case we go to show that the initial values do not influence the stability and the convergence of our proposed system. In this system we start out with users having different initial usage rates range from 1 (for User 1) to 10 (for User 10), in addition to this the users have contrasting WTP parameters wherein the user with highest initial demand (User 10) has the least WTP of 11 and User 1 has highest WTP of 20. We run the code iteratively and compute the new consumption rates for each user in each time slot.

The MATLAB code snippet for above is

```
not = 100;          %Number of time slots is set 100
a = 1;
k = 4;
C = 100;            %Setting the values for the involved parameters

x = [1:10]; %Initial demands start with 2
gamma = 0.2;        %Convergence parameter gamma
temp = zeros(not,10);%Temp store the demand rates of all users in all time
w = [20,19,18,17,16,15,14,13,12,11];        %wtp array for all 10 users

for t=1:not
    X = sum(x);     %overall demand X
    for n = 1:10
        x(n) = x(n) + gamma * (w(n) - x(n) * a * (X/C) ^ k);
        temp(t,n) = x(n);
    end
end
```

The simulation results are as follows:

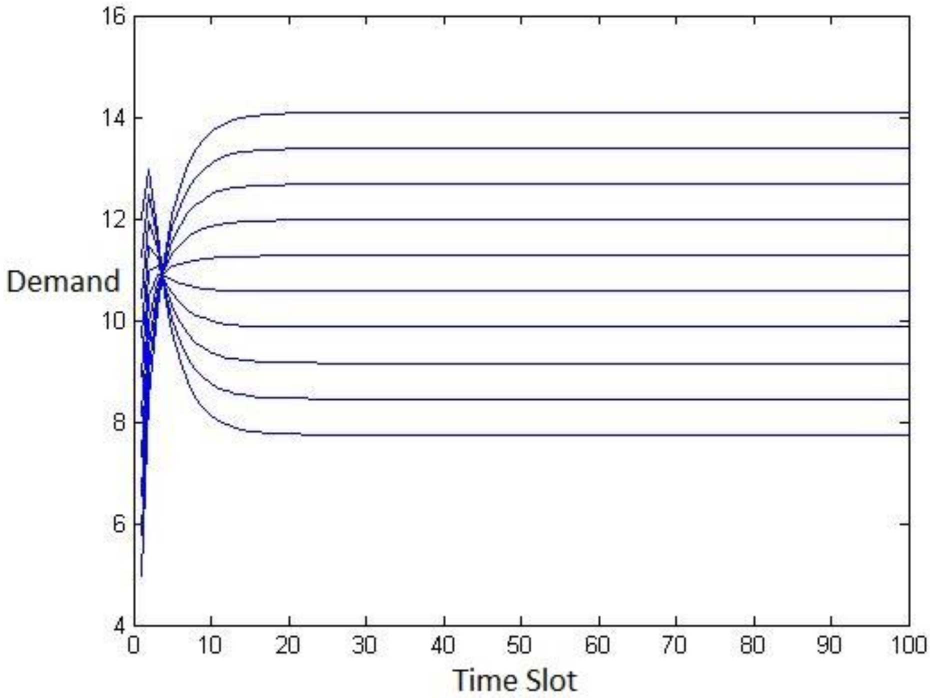


Fig 4.3: Users' initial demand adaptation based on WTPs

Similarly, the market price settles to equilibrium:

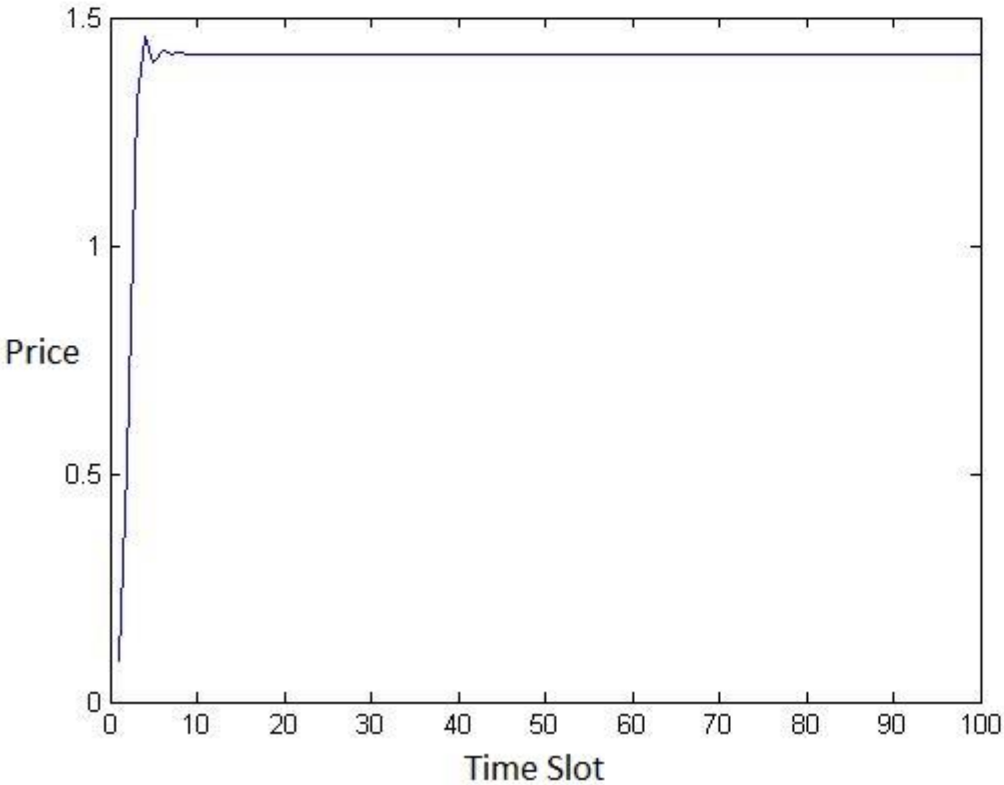


Fig 4.4: Converging market price

It is noteworthy that since all the market price influencing parameters such as a, k and C involved are similar between Case 1 and Case 2, the market price converges to the same value in both of these cases i.e. 1.42 units.

Case 2 makes it clear that initial system conditions have no role whatsoever in influencing the stability and convergence of our proposed system. The users will adapt their usage rates according to their WTPs when dynamic pricing is deployed. Also, based on these usage rates the market price itself will also reach an equilibrium point.

Case 3:

In this case, we deploy even more arbitrariness in our system, along with differing initial demands for all users, we also introduce a set of different WTPs, w_1 for the first 100 time slot and another set of WTPs w_2, for the next 100 time slots. The w_2 values are completely random as we use *rand (a,b)* MATLAB function to bring randomness to our model, this makes sense because in a practical scenario WTPs can be any random number and the supplier can't know them beforehand.

The MATLAB code snippet to model the above is

```
x = [1:10]; %Initial demands start with 2
gamma = 0.2;        %Convergence parameter gamma
temp = zeros(not,10);%Temp store the demand rates of all users in all time
w = [20,19,18,17,16,15,14,13,12,11];        %wtp array for all 10 users
price = zeros(1,not);

for t=1:100
    X = sum(x);     %overall demand X
    q = a * (X/C) ^ k;
    for n = 1:10
        x(n) = x(n) + gamma * (w(n) - x(n) * a * (X/C) ^ k);
        temp(t,n) = x(n);
        price(t) = q;

    end
end
w = w  -5 + (5+5)*rand(1,10);
for t=101:not
    X = sum(x);     %overall demand X
    q = a * (X/C) ^ k;
    for n = 1:10
        x(n) = x(n) + gamma * (w(n) - x(n) * a * (X/C) ^ k);
        temp(t,n) = x(n);
        price(t) = q;

    end
end
```

After running the simulation in MATLAB we get the following set of data:

Table 4.1: Users and their WTP parameters for different time slots

User #	***Initial Demand***	***WTP from t=0-100***	***WTP from t=101-200***
1	1	20	22.1
2	2	19	23.8
3	3	18	22.6
4	4	17	16.0
5	5	16	12.9
6	6	15	13.9
7	7	14	17.9
8	8	13	14.0
9	9	12	13.3
10	10	11	15.6

The plots obtained are as follows:

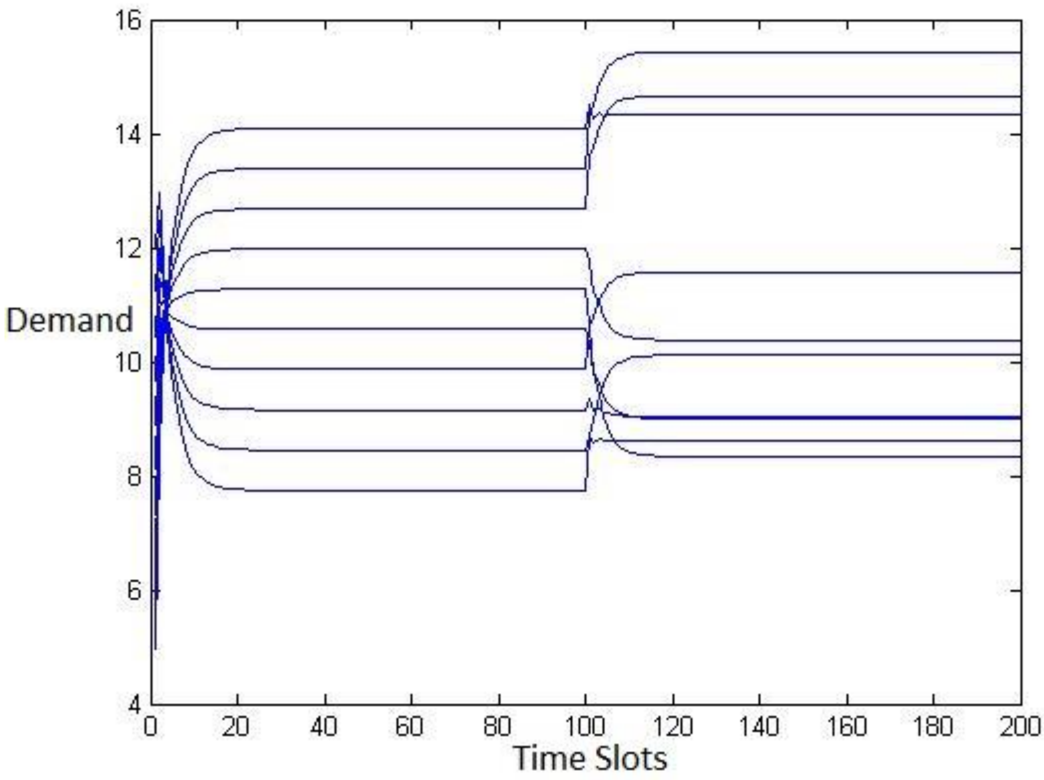


Fig 4.5 Varying WTPs and user demand adaptation

And the market price also quickly adjusts itself as users adapt their demands:

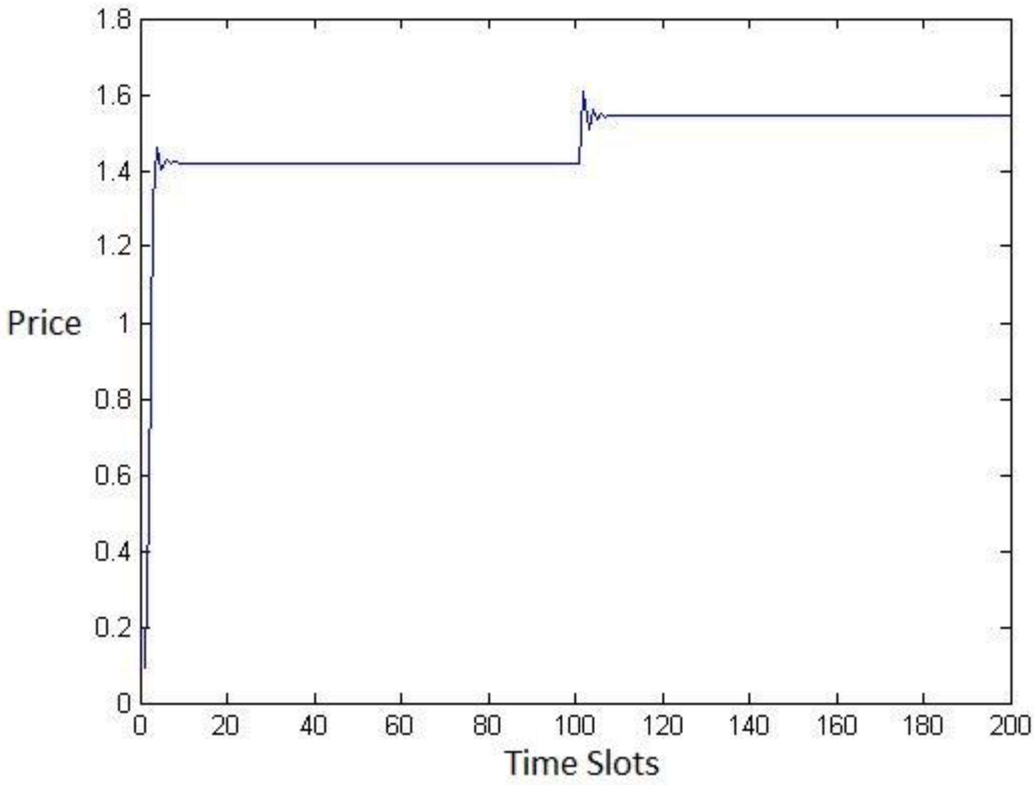


Fig 4.6: Adaptation of market price with a change in user demands

These test case simulations make it pretty clear that our proposed DR algorithm is fool-proof against any kind of initial conditions and remains stable under any kind of consumer behaviour. Its converging behaviour, dynamicity and stability makes it possible for us to use this algorithm further and test its suitability for PHEV charging. A more detailed perturbation analysis leaves scope for the future work in this field.

4.3. SUMMARY

We test the suitability of our proposed congestion pricing algorithm by checking it for convergence and stability under arbitrary market parameters. We establish that this algorithm can be used in the isoelastic market pricing model and so we can proceed to test its suitability for PHEV charging in the next section.

CHAPTER 5

APPLICATION OF THE PROPOSED ALGORITHM

5.1. OVERVIEW

In this chapter, we apply the proposed DR algorithm to the PHEV Charging and see how we can achieve our goal through shifting the demand to off peak hours. The overall model remains similar to the last chapter, however, demand *x* becomes the PHEV charging rate *x,* user *n* becomes PHEV *n* and rather than an individual responding to the prices w.r.t. his WTP we have a smart socket which is facilitated with bi-directional communication, this smart socket sends the WTP to the supplier and in return the PHEV receives a controlled charging rate based on its set WTP.

We also introduce the concept of state of charge as discussed in chapter 2, this soc value varies from [0,1] based on the amount of charge the PHEV battery has. The dynamics of PHEV battery charging is governed by the equation

$$y(n+1) = y(n) + (\alpha/B) * x(n) \tag{5.1}$$

where, y(n) represents the soc in time slot n, α is the battery charging efficiency and B is the battery capacity.

Through the following sections we perform simulations in three different case and show that this algorithm is not only suitable for Demand Response, but it also helps the consumers participating in this demand response program to save a significant part of their money. Of course, the amount of money that can be saved requires a deeper study of its own as machines are becoming smarter each day and new study fields such as Machine Learning and predictive analytics etc. are gaining wider interest. We also show how the smart socket can be designed to adjust the WTP parameters on its own such that the PHEV finishes its charging by the time of set departure.

5.1.1 DATA USED FOR SIMULATION

In this chapter we assume that there are 100 PHEVs actively participating in the DR program. All PHEVs have a battery charging efficiency of 85%, the unit of charging rate is set as 100kW and the initial soc is set as 0.15 unless otherwise mentioned. The time period is discretely divided such that there are 100 slots in a one hour period. The Battery capacity, B is 10kWh.

5.2. MODEL SIMULATIONS IN PHEV CHARGING

Cases: In this case we see how the overall demand curve looks like for various values of WTP parameters for PHEV agents. We then do a similar simulation but this time for a completely random set of WTPs, again we use *rand* MATLAB function to achieve this randomness. We see if this algorithm helps in achieving the Demand Response through this case.

(i) To start with we assume that the WTPs are set such that for each user *i*, $w = 0.01 + 0.01 * i$, soc is assumed to be set as 0.15 for all users. We incorporate the soc formulation in our algorithm and set a condition that when soc = 1, the PHEV disconnects from the grid and its charging rate drops to 0.

The MATLAB code is shown below, note the *if-else* statement which enforces the charging dynamics:

```
for i = 1:100
    w(i) = 0.01 + 0.01*i;
end

for t=1:not
    X = sum(x);      %overall demand X
   % soc(n) = soc(n) + (alpha/B)* x(n);
    for n = 1:100

        if soc(n) <= 1
            x(n) = x(n) + gamma * (w(n) - x(n) * a * (X/C) ^ k);
            soc(n) = soc(n) + (alpha/B)* x(n);
        else
            x(n) = 0;
        end
     overallDemand(t) = X;
    end

end
```

The following simulation plot is obtained:

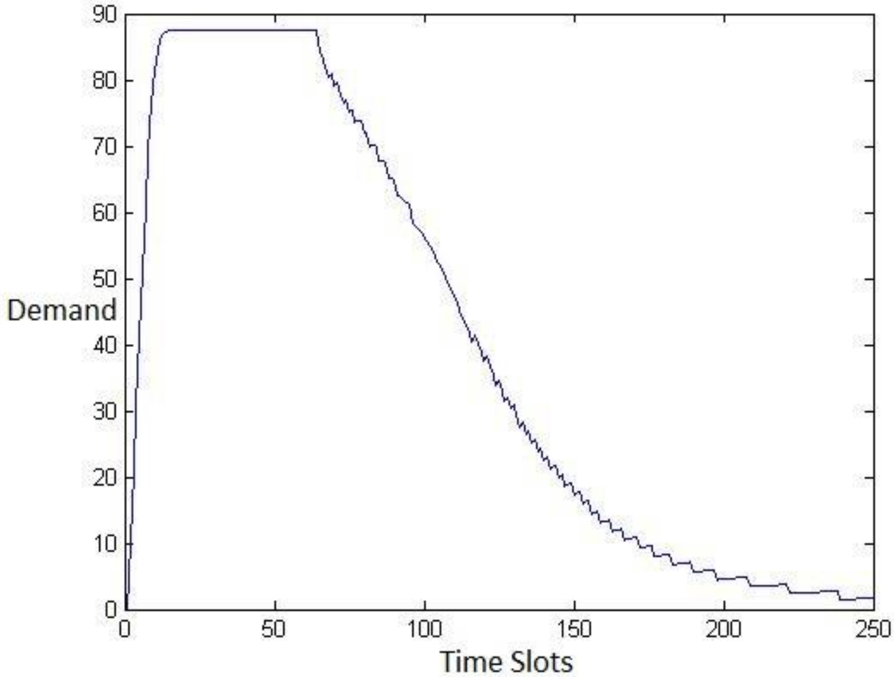


Fig 5.1: Overall Demand for 100 PHEVs

From the above plot it can be clearly seen that the demand keeps constant until the 60th time slot, then as the PHEVs start completing their charging and soc becomes 1, they are disconnected from the grid and the overall demand keeps reducing.

(ii) For a more realistic scenario, let us randomize the WTPs to a value between [0,2]. In this case the following plot is obtained:

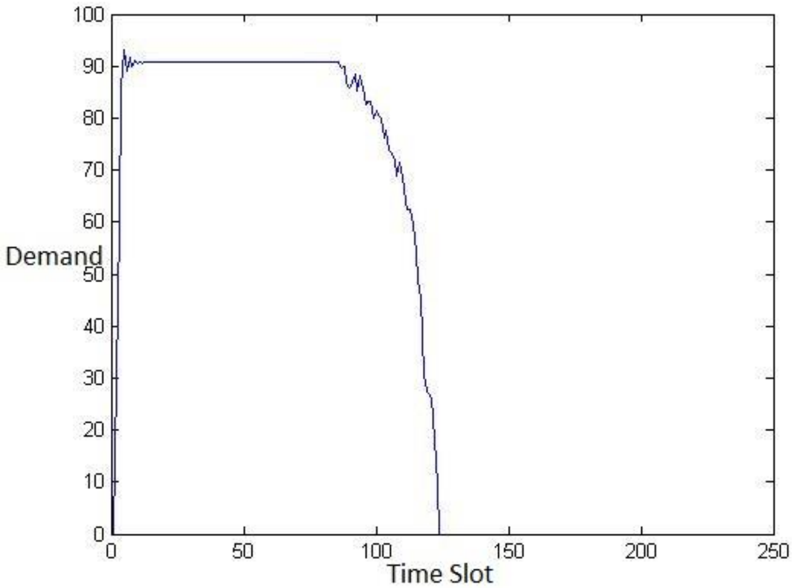


Fig 5.2: Valley filling obtained through our DR algorithm

Note: The significance of the above plot is that randomized WTPs come close the resembling a scenario with large number of PHEV participants, here we can clearly see that a close to ideal valley filling process has occurred. This brings a great possibility of satisfying maximum amount of user demand with limited infrastructure as the *Peak Average Ratio* is 0.91.

(iii) In the last part, we also randomize the initial soc values for all PHEVs in the range of [0.15,0.35] and observe the results:

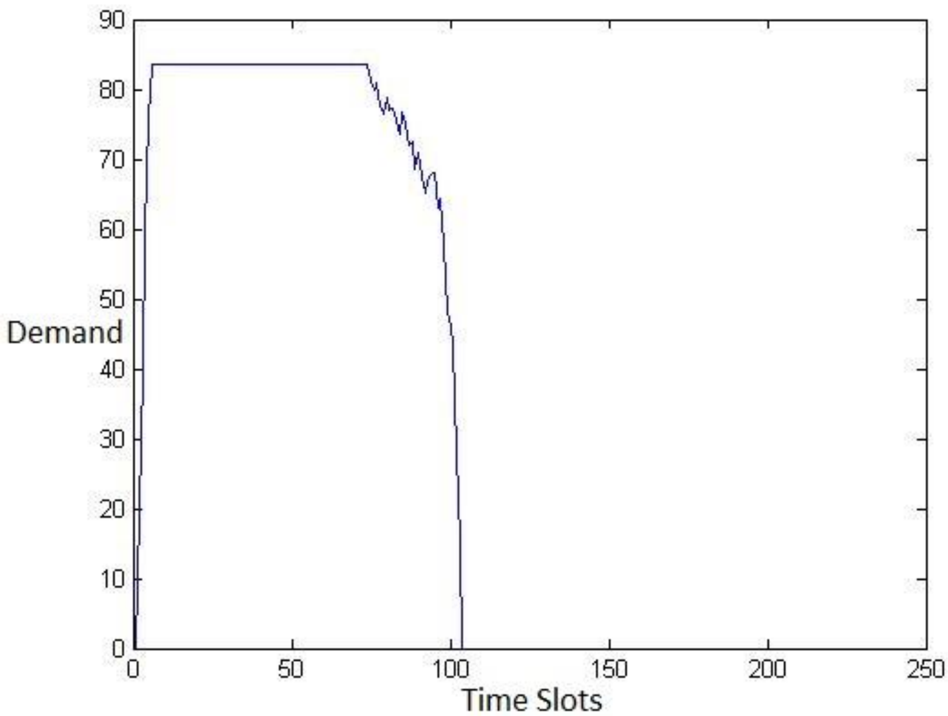


Fig 5.3: Effect of initial SOCs on the overall demand pattern

The purpose of this simulation is to show the prevalence of initial socs on the overall load pattern. It can be seen that this case finishes charging before (ii) because there are some PHEVs present in this case which are already charged higher to some extent.

5.3. SMART PHEV CHARGING WITH DR

We now introduce a way of charging PHEV such that the WTP parameters are fed by the smart socket itself.

Let us say that the user of PHEV want the charging to be done before their set departure in one hour i.e. time slot 100. How do they go about programming the smart socket to finish their charging by the scheduled time? The answer lies in the charging dynamics equation discussed earlier. Let's assume that the charging needs to be done by time t_{ch} , then from

$$y(n+1) = y(n) + (\alpha/B) * x(n)$$

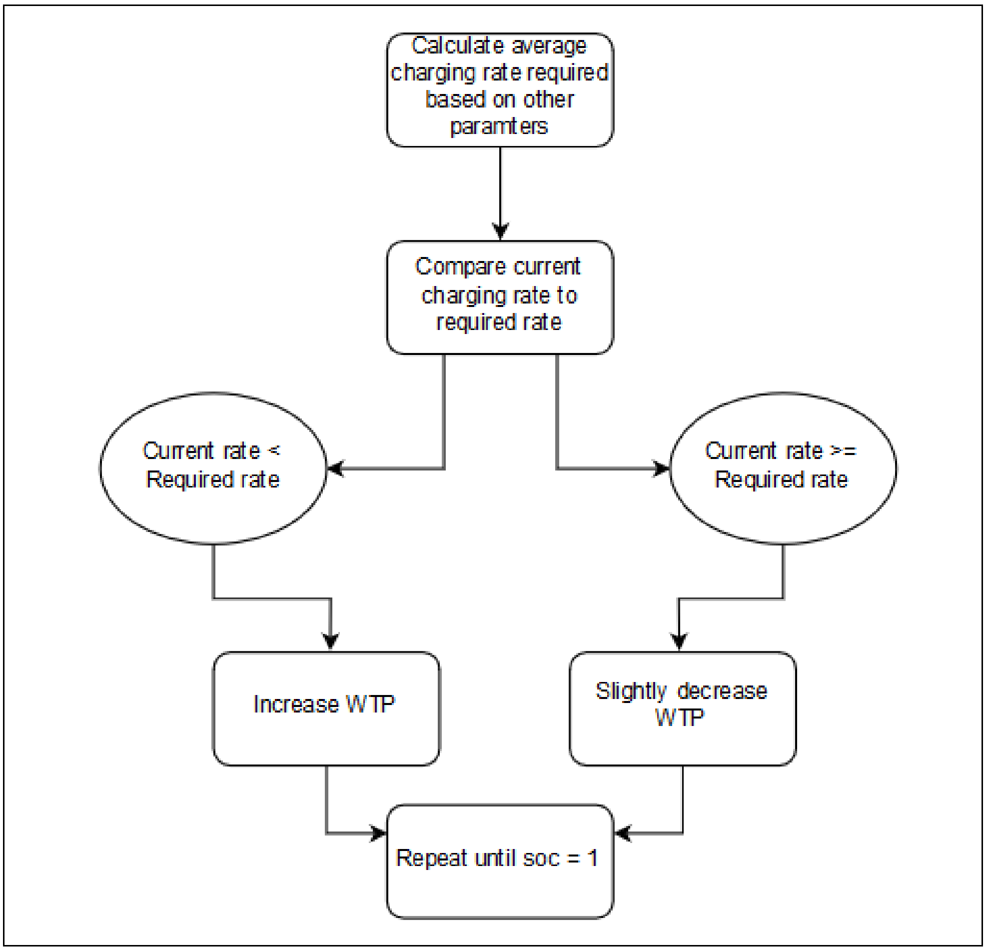
we obtain,

$$y(t_{ch}) = y(n) + (\alpha/B) * x_{avg}(n) * t_{ch}; \qquad y(t_{ch}) = 1$$

rearranging gives us average required charging rate for finishing charging before departure:

$$x_{avg} = B\,(1 - y(0)) / \alpha\, t_{ch}$$

Simulation case: Let us assume that a PHEV charging needs to be done by time slot 100 and the initial soc is 0.15. To solve this problem, we use repetitive iterations to ensure that the charging rate never drops below x_{avg}, whenever it drops we increase the WTP for that PHEV slightly and check again in the next time slot.



The MATLAB code for the same where PHEV 100 tries to finish its charging before t = 50 in our set of parameter values is formulated below

```
for i = 1:n
    reqRate(i) = 100*(1-soc(n))/(0.85*50);
end



for t=1:not
    X = sum(x);      %overall demand X
   % soc(n) = soc(n) + (alpha/B)* x(n);
    for n = 1:99

        if soc(n) <= 1
            x(n) = x(n) + gamma * (w(n) - x(n) * a * (X/C) ^ k);
            soc(n) = soc(n) + (alpha/B)* x(n);
            state(t,n) = soc(n);
        else
            x(n) = 0;
            state(t,n) = soc(n);
        end
    end
        for n=100
            if soc(n) <= 1
                if x(n) < reqRate
                    w(n) = w(n) + 0.5;
                    elseif x(n)>=reqRate(n)
                    w(n) = w(n) - 0.1;
                end
                x(n) = x(n) + gamma * (w(n) - x(n) * a * (X/C) ^ k);
                soc(n) = soc(n) + (alpha/B)* x(n);
                state(t,n) = soc(n);
```

Here in the code, 99 PHEVs are following their routine DR participation but PHEV 100 wants to finish its charging by t = 50. We run the soc simulations and compare between PHEV 99 and PHEV 100. If the algorithm works well then the PHEV 100 should reach soc at t = 50 and other PHEVs should take their normal time to continue best with the DR algorithm.

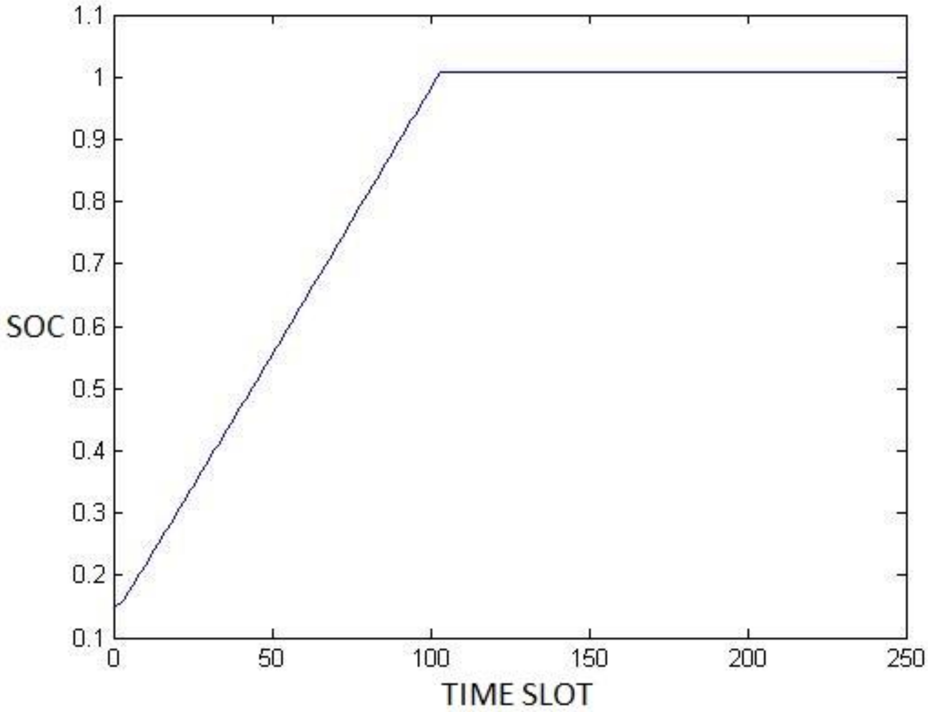


Fig 5.4 SOC vs Time plot of a normal PHEV

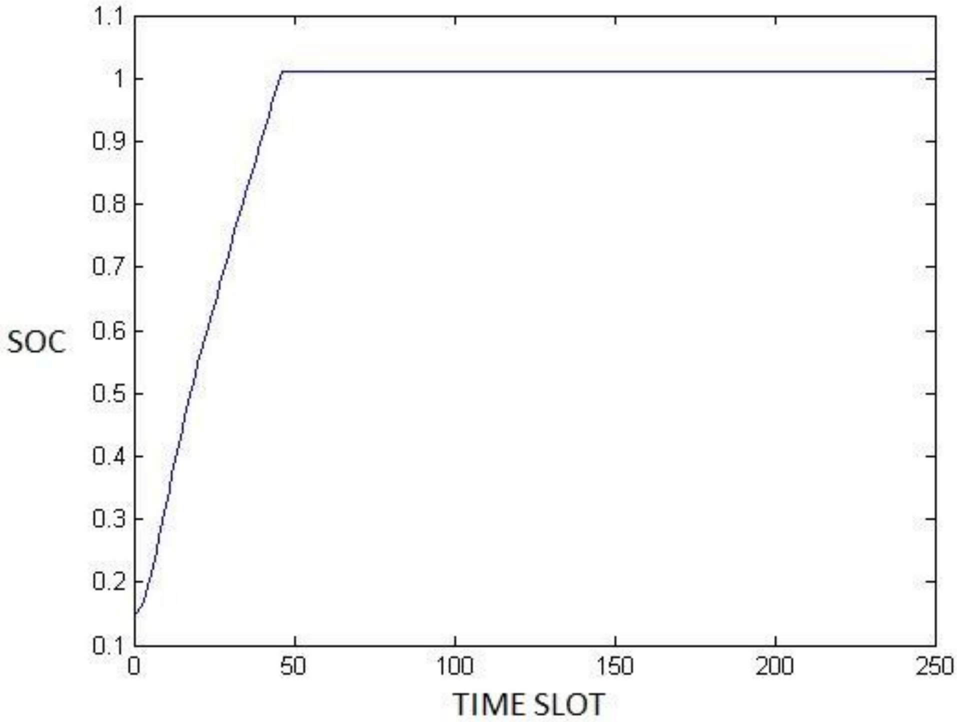


Fig 5.5 SOC vs Time plot of PHEV 100, departure time is t = 50

It is evident from the above two graphs that the program is working and that smart sockets can in fact, adapt WTPs on their own to meet the user needs.

With the growing knowledge in the fields such as Machine Learning and Statistics, it is very likely that a more advanced program would be able to automatically adapt the WTPs for the user 24/7. However, in rushing the charging completion before t=50 and not participating in the DR algorithm to the fullest PHEV 100 does incur higher cost than the other PHEVs. Based on this experiment the price function of the two PHEVs; PHEV 100 and PHEV 99 are given below.

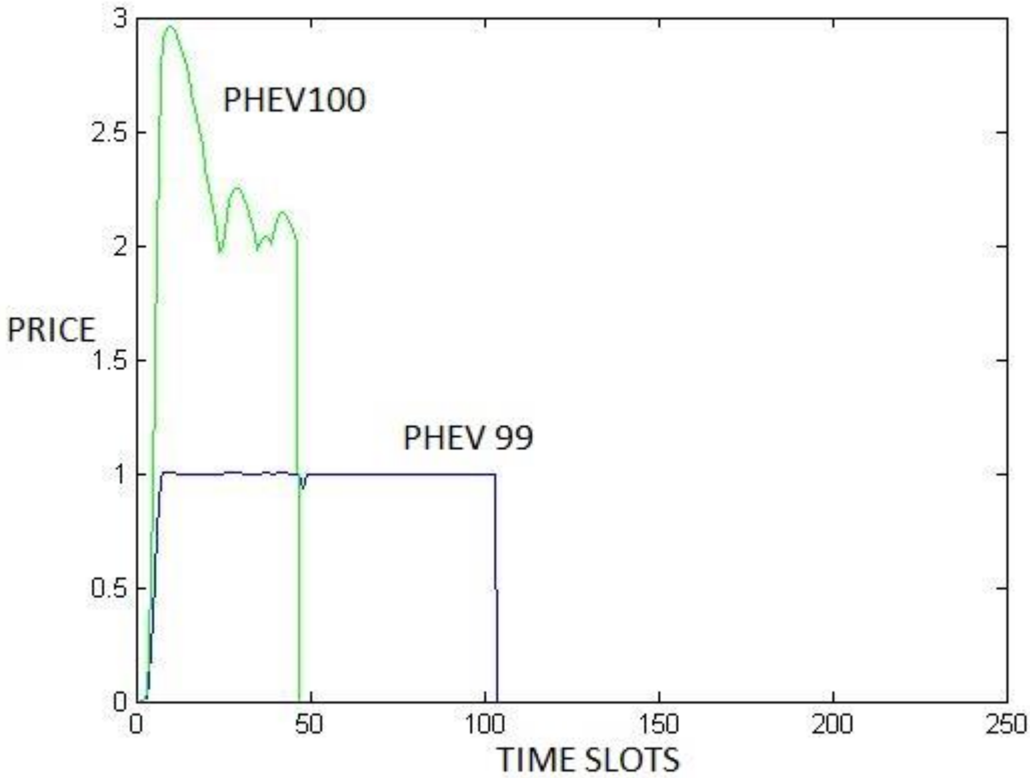


Fig 5.6 Price function vs. Time for PHEV100 & PHEV99

It should be **noted** that although the price function of PHEV100 is considerably higher than PHEV99, the overall difference in the cost incurred between the two is not that high. In fact, in this case the difference is roughly 4% between the total prices incurred. It is due to the fact that although PHEV 100 costs much higher but its charging is finished in less than half the time it takes to charge the other PHEVs.

However consider an another PHEV which doesn't participate in the DR program and just wants the charging done in 50^{th} time slot without caring about the dynamics of the market. Then depending on the time of the day, that PHEV can incur a cost of charging significantly higher than the other PHEVs.

5.4. SUMMARY

We applied our model to PHEV charging and acknowledged its suitability in various market scenarios; we also tested our model's convergence for a varying WTP with time. In the previous section, we devised a method through which smart sockets can be programmed to adjust WTPs on their own to get the charging done before the set departure time.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. CONCLUSION

The motivation behind the project was to come up with a demand response algorithm to meet the needs of a growing PHEV market through the least investment in infrastructure. We started off by saying that to meet the most demand through a limited supply capacity, the Peak Average Ratio of the demand side should be as close to 1 as possible.

We approached the idea of congestion pricing in a dynamic market and converted it into a weighted demand supply equation where users have a willingness to pay and based on that they are free to choose but they will concede more cost when the resources are more congested. To formulate this we assumed that our market is an iso-elastic price market and that the price is a function of the total overall demand from all users. Naturally, users would react to the prices based on their price sensitivity convergence parameter and the feedback marks i.e. the market price incurred for their current demand.

We took the above idea and simulated the algorithm for various values of the involved parameters such as the initial demands, heterogeneous convergence parameters and time varying WTPs to prove that the algorithm is in fact robust and ready to be applied into our DR for PHEV because of its tendency to converge and the stability under various practical conditions.

We then applied this algorithm to PHEV Charging, instead of the consumer we had a smart socket to react to the WTP and market pricing. It communicates with the supplier and the charging rate is adjusted. We saw the simulations for different values of WTPs for a group of 100 PHEVs considered as a market and found that the Peak Average Ratio is close to 1, which is great from a demand side management point of view.

We then went on to make the smart sockets even smarter by devising a program which can adapt WTPs on its own so as to meet the charging rate requirements as set by the user side. Here, we calculated the average minimum charging rate required and then we tweaked WTPs such that the charging rate never falls below the minimum requirement.

6.2. FUTURE SCOPE

We have carried these simulations in small Home Area Network with a rather small number of PHEV participants, but have not discussed the possibility of a larger market where the PHEVs can absorb the power and sell them back to the grid to cancel out the demand fluctuations. This leave scope for the integration of intermittent and unstable Renewable Energy sources into the grid.

Our model is such that the actions of each user will have an impact on the behaviour of the other user, it will also decide the market price which means that everyone is influenced by everyone else. This leaves scope for game theory based analysis of the network. This will help implement fairer incentive mechanisms from the seller as he will know the buyers well.

We also understand that in a large market, study of the historical data will enable users to learn so they can predict the future load and prices to maximize the savings. Hence, it can be envisaged that topics such as Reinforcement learning and predictive analytics will contribute in making the market highly dynamic in years to come.

REFERENCES

1. Hota, Ashish Ranjan, Mahesh Juvvanapudi, and Prabodh Bajpai. "Issues and solution approaches in PHEV integration to smart grid." Renewable and Sustainable Energy Reviews 30 (2014): 217-229.

2. Medina, Jose, Nelson Muller, and Ilya Roytelman. "Demand response and distribution grid operations: Opportunities and challenges." IEEE Transactions on Smart Grid 1.2 (2010): 193-198.

3. A.Ganesh, K. Laevens, andR. Steinberg, “Congestion pricing and user adaptation,” in Proc. IEEE Infocom, 2001

4. Fan, Zhong. "A distributed demand response algorithm and its application to PHEV charging in smart grids." *IEEE Transactions on Smart Grid* 3.3 (2012): 1280-1290.

5. A. Mohsenian-Rad, V. Wong, J. Jatskevich, and R. Schober, “Optimaland autonomous incentive-based energy consumption scheduling algorithm for smart grid,” in Proc. IEEE ISGT, 2010.

6. Stephen Chapman, “MATLAB Programming for Engineers”

7. PHEV data:
   https://www.mitsubishicars.com/outlander/specifications
   www.chevrolet.com/volt-electric-car

8. G. Vinnicombe, “On the stability of networks operating TCP-like congestion control,” in *Proc. IFAC*, 2002.

9. Wang, Jianhui, et al. "Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power." *Energy Policy* 39.7 (2011): 4016-4021.

10. Li, Na, Lijun Chen, and Steven H. Low. "Optimal demand response based on utility maximization in power networks." *Power and Energy Society General Meeting, 2011 IEEE*. IEEE, 2011.

11. Ban, Daehyun, George Michailidis, and Michael Devetsikiotis. "Demand response control for PHEV charging stations by dynamic price adjustments." *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*. IEEE, 2012.

12. Mallette, Megan, and Giri Venkataramanan. "Financial incentives to encourage demand response participation by plug-in hybrid electric vehicle owners." *Energy Conversion Congress and Exposition (ECCE), 2010 IEEE*. IEEE, 2010.

13. Shao, Shengnan, Manisa Pipattanasomporn, and Saifur Rahman. "Grid integration of electric vehicles and demand response with customer choice." *IEEE Transactions on Smart Grid* 3.1 (2012): 543-550.

14. S. Gormus, P. Kulkarni, and Z. Fan, “The power of networking: How networking can help power management,” in *Proc. 1st IEEE Int. Conf. Smart Grid Commun.*, 2010