VEHICLE-TO-GRID (V2G) INTEGRATION WITH THE POWER GRID USING A FUZZY LOGIC CONTROLLER

by

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Abstract

This thesis introduces a Vehicle to Grid (V2G) system which coordinates the charging, and discharging among the Electric Vehicles (EVs) and two-test systems, to help with peak power shaving and voltage stability of the system. Allowing EVs to charge and discharge without any control may lead to voltage variations and disturbance to the grid, but if the charging and discharging of the EVs is done in a smart manner, they can help the power network. In this thesis, fuzzy logic controllers (FLC) are used to control the flow of power between the grid and the electric vehicles.

The presented work in this thesis mainly focuses on the control architecture for a V2G station that allows for using EVs batteries to help the grid's voltage stability. The designed controllers sustain the node voltage, and thus also achieve peak shaving. The proposed architectures are tested on 16 -generator and 6-generator test systems to examine the effectiveness of the proposed designs. Five fuzzy logic schemes are tested to illustrate the V2G system's ability to influence system voltage stability.

The major contributions of this thesis are as follows:

- FLC based control tool for V2G station present at a weak bus in the system.
- Investigate the effect of the station location and voltage sensitivity.
- Comparison of chargers providing real power versus reactive power.
- Simulation of controller and system interactions in a daily load curve cycle.

Keywords: State of Charge (SOC), Electric Vehicle (EV), Fuzzy Logic Controller (FLC), Vehicle to grid (V2G), and Power System Voltage Stability.

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Dedication

To my Parents, Mofleh and Ghozyel Alshogeathri, whose encouragement was a great source of inspiration for me, to my whole family for their supportive messages and encouragement.

Chapter 1- Introduction

In this chapter, we determine the setting for the problems we deal with in the thesis. We start by discussing the motivation for the work presented in the thesis and discuss the vehicle to grid technology. We also discuss the motivation of using fuzzy logic and voltage stability phenomena in regards to the thesis. We then provide a short outline of the remainder of the thesis.

1.1 Research Motivation

The present-day electric power grid is experiencing a major overhaul for the first time since its beginning over a hundred years back. These changes are aimed at not only improving its overall functionality but also positively impacting the lives of the millions of people who are in one way or another dependent on it. Making the smart grid a reality will involve the improvement of the existing power related infrastructure, as well as the introduction of new technology to work in conjunction with the existing infrastructure. It is widely believed that electrical vehicles (EVs) will be a vital component to make the smart grid a reality. EVs have a number of features that make them an attractive option to both the smart grid and the EV user as well. The defining characteristic of EVs that has placed them in the current grid spotlight is the Vehicle to Grid (V2G) feature. EVs need to charge and draw power from the grid when the State of Charge (SOC) of their batteries reaches low levels. The V2G property of EVs would also allow EVs to deliver power back to the grid. The EV features that would be beneficial to the smart grid are [1, 2, 3]:

I. Bidirectional power flow between EV and the grid would help meet power requirements during periods of peak load demand.

II. Also, the bidirectional property could be used in order to selectively charge the EVs when the grid is at off peak hours.

III. Help in improving power quality and stability by providing real and reactive power when necessary.

Similarly, EVs are beneficial to the users in the following ways:

I. They are a source of revenue for the user via the V2G feature.

II. EVs have greater fuel efficiency as compared to regular vehicles, which further reduces the vehicle related expenditure for the users.

1.2 Vehicle to Grid Technology

Voltage to Grid technology can be described, as a system in which there is the ability to control bi-directional electrical energy flow between a vehicle and the electrical grid. The electrical energy flows from the grid to the vehicle in order to charge the battery. It flows in the other direction when the grid requires the energy, for example to provide peaking power. With bi-directional chargers, electric vehicles have the potential to play the V2G role, and the vehicle becomes an asset in a smart grid. By utilizing the V2G network, the public utilities can provide a more stable and better-controlled service to meet sudden rises in demand and store energy for future use when supply is high.

V2G systems could also provide financial benefits to owners, thus reducing the overall costs of purchasing an electric vehicle. Vehicle to Grid systems allow vehicle owners to generate revenue from selling power back to the grid [4]. In this thesis we design V2G systems to improve the voltage stability of power systems.

1.3 Motivation for Using Fuzzy Logic

Finding an easy and simple model to describe the dynamic behavior of the power system network and its control systems is extremely problematic. This is due to the nonlinear nature of the network, its large size, its interconnectedness, and its varying time scales. Operating conditions for the power system change constantly and disturbances in the power system vary from one system to another. For these reasons making accurate calculations of the power system network is difficult. Fuzzy logic is utilized in this thesis as an efficient method to deal with the nonlinear, changing, and unpredictable power system network.

Fuzzy logic is an easy method used to solve issues with the behavior of the power system network because it is flexible and depends on the "fuzzy sets" made for the inputs and outputs based on the estimations of the user. Lotfi Zadeh, who is considered to be the father of fuzzy logic stated, "In almost every case, you can build the same product without fuzzy logic, but fuzzy is faster and cheaper" [5].

1.4 Voltage Stability

It is vital that at any given period, a power system operating condition should be stable, should meet various operational criteria, and it should also be secure in the event of any credible incident. Current power systems are functioning closer to their stability limits due to economic and environmental constraints and pressures. Maintaining the stability of the power system is a very important and challenging issue. Voltage instability has been of great concern to power system researchers in recent years, and is being considered as one of the major causes of power system uncertainty. Voltage instability occurs when voltage falls below its normal value and does not recover even after setting and restoring some of the power system devices such as VAR compensators. Voltage collapse is the manner by which the voltage falls to a low, undesirable value, thus resulting in voltage instability [6]. Heavier loading can be considered one of the major causes of voltage instability when associated with a fragile system (voltage and VAR problems).

1.5 Thesis Organization

This thesis is organized as follows. Chapter 2 reviews the literature related to the research and fundaments. Chapter 3 highlights the engineering problem at hand and introduces the research plan and steps taken to achieve the proposed work. Chapter 4 discusses the analysis and research results. Chapters 5 summarizes the results from all the simulations, make conclusions and discusses the future work that can be done to maximize the use of this Vehicle to Grid technology.

Chapter 2 - Literature Review and Fundamentals

2.1 Literature Review

Power system voltage stability involves generation, transmission, and distribution. Voltage stability describes a power system's ability to maintain appropriate voltage levels when small or large disturbances happen to the system. In today's power systems, heavier loading in both real and reactive power can be considered one of the major causes of voltage instability [6].

Vehicle-to-grid technology is becoming an active player in grid operations and plays an important role in improving the stability, reliability and environmental aspects of grid system operations [7]. EVs can also serve as an energy resource through V2G operation by sending electricity back into the grid thereby preventing load shedding [7, 8].

Ideal scheduling for charging and discharging of EVs in V2G framework is developed in [9]. In that paper, a scheduling optimization problem is discussed where charging powers of the EVs are improved to minimize the total charging cost of all EV's, which perform charging during the day. Through the authors' simulations, they have demonstrated that the locally optimum scheduling scheme can achieve a close performance compared to the globally ideal scheduling structure [9].

A V2G concept has been explored through simulation of a typical distribution system [10]. In this paper, the concept of a charging station is introduced where all EVs from a particular area will charge or discharge their energy to the grid from the same location. With high penetration of electric vehicles, stability of the electric grid becomes a challenging task. To manage this challenge, a V2G controller and a charging station controller have been designed using fuzzy logic. These controllers have been used to control the flow of energy between EVs and the grid. FLC has been implemented to achieve V2G operation, and the impact of this V2G operation in terms of peak demand management and voltage regulation [10]. The results were demonstrated for a distribution system of Guwahati city, which is part of the North Eastern Regional Grid of India.

A charging station for the electric vehicle has been proposed in [11]. The charging station can handle 50 EVs with different SOC limits and with different energy ratings. An algorithm has been proposed which takes care of the SOC limit while discharging the batteries' energy to the grid. Peak shaving can also be obtained using the proposed charging station. From the simulation results, it is observed that the flow of the current in the battery changes as per the power requirement by the grid, which is brought in as a remote signal [11].

L. A. Zadeh first founded fuzzy logic in 1965. At first fuzzy logic did not gain much attention but now it is widely using in many areas. Its flexibility to handle problems that are vague in nature makes it very efficient and appropriate for complex system analysis [5].

From the above discussions, it is assessed that the researchers have successfully studied and demonstrated the V2G charging and discharging behavior to control the voltage of a bus. However, the real time implementation of the individual EV and their interactions with system loads and for grid support still needs further investigation.

2.2 Fundamentals of Fuzzy Logic

Fuzzy logic and fuzzy sets are used in order to convey and work on facts that are not precise and where the analysis depends heavily on the opinion of the user as opposed to facts which are certain and definite [5]. Generally people do not describe concepts such as quality, strength, and weakness in definite terms. Rather, most concepts are described by people in vague and imprecise terms.

When it comes to classical set theory, a statement is either true or false, which correspond to a logical value of 1 and 0. This is why it is unable to handle such human concepts such as false being divided into categories ranging from very false to not quite false. Fuzzy logic is closer to how people describe concepts, and it uses words as opposed to numbers in defining variables. It allows for more flexibility and accuracy when describing many complex systems [5].

There are several essential characteristics of fuzzy logic [5]:

I. In fuzzy logic, everything is a matter of degree.
II. Any logic system can be fuzzified.
III. Facts are interpreted as a collection of fuzzy constraints on a collection of variables.

The major elements of fuzzy logic can be summarized as follows:

I. Fuzzy sets
II. Membership function
III. Fuzzy Rules
IV. Fuzzy Inference System

2.2.1 Fuzzy Sets

Normal sets have a defined grouping. Something is either included or excluded which means that the set membership values are either “1” or “0”. Fuzzy sets however are not defined in such manner; instead they belong in a range with the values between zero and one describing the degrees to which a value is included in a set [12].

To explain this concept, here is an example. For a height of a person, being a tall or a short person depends on different standards. Under common opinion an adult male who is more than 6 feet high can be called “tall”, while one less than 5 feet and 5 inches is “short”. Below we can see how we can use fuzzy set phenomena to solve this problem [12]:

-Is 6’3 tall?

--True: degree=1

-Is 5’3 tall?

--False: degree=0

-Is 5’10 tall?

--Partially true: degree= .85 (tall but not completely)

-Is 5’7 tall?

--Partially true: degree= .30 (not as close as 5’10)

2.2.2 Membership Functions

A membership function is a curve that defines inputs and outputs in terms membership degree. The shape of the function depends heavily on the type of problem and its inputs as well as the experiences of the logic designer. The curve however only varies from "0" to "1". After a membership function is established, fuzzy rules are then designed in order to make a decision about the output results. There are 11 functions commonly used to build membership functions in the Matlab fuzzy logic toolbox [12]. The shape used in this thesis is the triangular membership function (trimf).

2.2.3 Fuzzy Rules

The fuzzy rule or the "If-then rule" is a basic concept in fuzzy logic that is based on the intuition of the user for the actual application. When the fuzzy rules are established, the outputs of the system follow the description of the user. Therefore the outputs are adequate and acceptable as long as the knowledge about the system is accurate. After the inputs are fuzzified and the fuzzy rules are applied, the outputs for each fuzzy rule become fuzzy sets. Defuzzification, the process of converting a fuzzy variable into numeric values is finally done in order to obtain outputs that make sense practically [12].

A fuzzy control rule is based on the knowledge of the actual application. It is usually expressed in logic of IF-THEN sequence to describe the actions and the outputs of a system given the detected information [13]. And normally it can be expressed as

"IF (a specific set of conditions are fulfilled), THEN (a set of consequences can be implemented)."

To explain the concept of fuzzy rules, here is an example:

"IF the grid is in LOW NEED of power, and the SOC of the battery is of LOW level, THEN the discharging rate should be……."

In this example the inputs are grid power need and battery SOC, while the output is the discharging rate.

The output of each rule is a fuzzy set. Then the outputs are aggregated into a single set, and the process is called "defuzzification." After the defuzzification process the final output will be in form of a single value [12].

2.2.4 Fuzzy Inference System

A Fuzzy Inference System (FIS) is a system that includes all the major elements mentioned in the previous sections:fuzzy set, membership function and fuzzy rules. The fuzzy inference system is the process of formulating the mapping from a given input to an output using a fuzzy logic. There are two basic types of Fuzzy inference system [12]:

- Mamdani type
- Sugeno type

The FIS used in this thesis is a Sugeno type. The advantages of using the Sugeno method are that it is more equations based, has widespread acceptance, and is better suited to use in MATLAB. In the Sugeno method output membership is defined by polynomial equations of varying degrees. A typical fuzzy rule in a Sugeno fuzzy model has the form [12]:

$$\text{if } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = p*x + q*y + r$$

In this thesis we used a zero order Sugeno which is a constant, $z = k$.

2.2.5 Fundamentals of Fuzzy Logic Controller

The fuzzy logic based system's complexity increases rapidly with increase in the number of inputs and outputs. A Sugeno type Fuzzy Logic Controller [14] has been designed in this thesis (see Fig. 2.1).

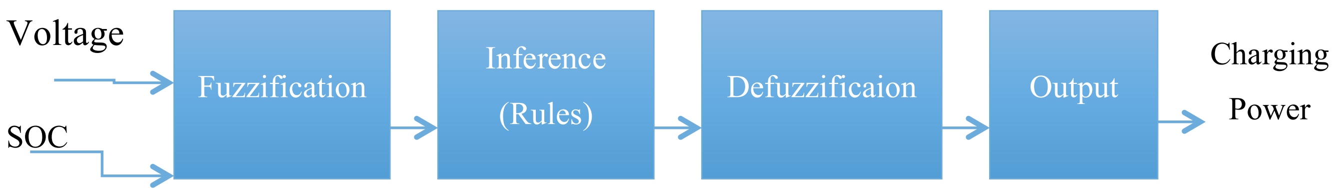

Figure 2.1 Fuzzy Logic Controller [14]

As shown in Fig. 2.1, a FLC consists of four key components: a fuzzification stage, an Inference (rule base) stage, a defuzzification stage, and lastly an Output stage. The fuzzification stage converts the binary logic inputs into fuzzy variables, while the defuzzification stage converts the fuzzy variables into binary logic outputs. All of this conversion is accomplished by ways of a membership function. The rule base stage is the collection of IF-THEN rules that describe the control strategy agreed upon. The output from each rule in the rule base is constructed by the inference logic to attain a value for each output membership function [15].

2.3 Load Curve Theory

A load curve is a chart used by power manufacturers and engineers to show how much electricity customers as a group consume during a given period of time (Fig. 2.2). When looking at the chart, time typically is placed on the horizontal axis, and the load power is placed on the vertical axis. This data can be used to forecast power trends, which allows an area to build and connect necessary power generators for peak demand periods.

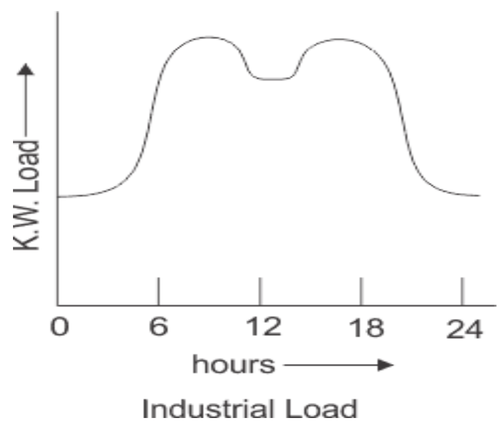

Figure 2.2 Example of a load curve [16]

Power stations use daily, monthly and yearly load curves to determine the amount of generators needed to meet demand. Daily load curves look at a 24-hour period of time to find the load requirements usually every hour or half-hour. The highest point on a load curve is the maximum demand at a given point in time. The area under a curve is the amount of energy units that were generated during that period of time. To help meet power demands, power stations can be connected in different ways throughout the year in an certain area. Types of power generators used differ depending on the resources in a geographic area. Some of the power generator types include photo voltaic, wind, coal, nuclear, steam, hydro and gas turbine. In most cases, the most efficient power generators are run all of the time with less efficient, more costly plants used only for peak demand times, based on the information collected or interpreted from the load curve.

The load curve data analysis used in this thesis is estimated and scaled from a central Florida load curve researched by the Florida Solar Energy Center [17]. The data from the central Florida load curve is constructed by collecting detailed electricity end-use load data by monitoring 204 residences in central Florida. The load curve used in this thesis is estimated and scaled to get a normalized daily load curve such that the maximum load value is 1.2833 pu as seen in Fig. 2.3.

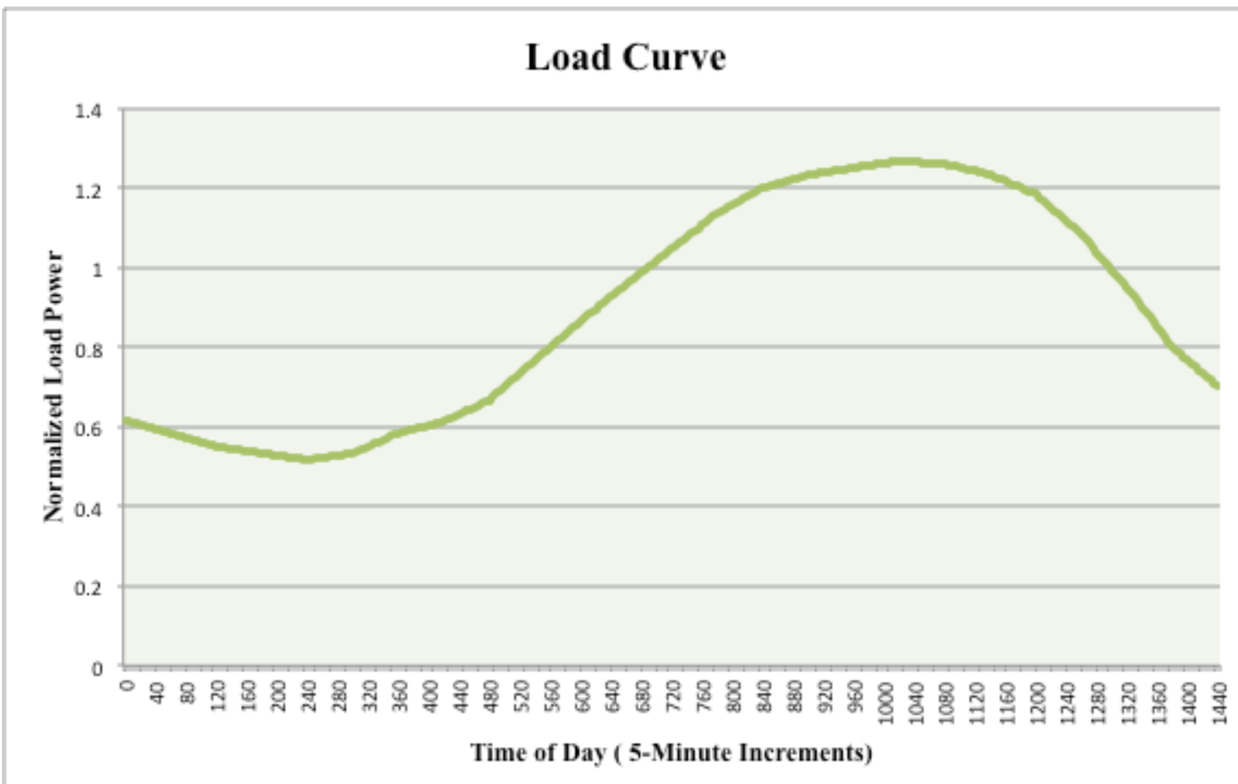

Figure 2.3 Normalized Load Curve

For each system, we picked a scale factor based on trial and error with the goals of applying significant stress to the system but still allowing the loadflow to converge. For the 16-generator test system, the normalized load curve is multiplied by 1.05, while for the 6-generator test system the load curve is multiplied by 1.1. We multiplied both P and Q of the load by these factors to maintain a constant power factor.

The charging demand analysis for the State of Charge (SOC) used in this thesis is estimated and scaled from a Nordic region uncontrolled all day EV demand curve [18]. The Nordic region includes Denmark, Finland, Norway and Sweden. The uncontrolled charging all day refers to the approach that EVs can be charged whenever they are parked during the day regardless of the parking place or time of day, etc. The driving pattern analysis is based on data from the National Travel Surveys of Denmark, Finland, Norway and Sweden. The charging demand curve used in this thesis is estimated and scaled to get a normalized SOC demand curve such that the maximum state of charge for the array is 0.9 pu. and the minimum SOC demand value is 0.4 pu. as seen in Fig. 2.4.

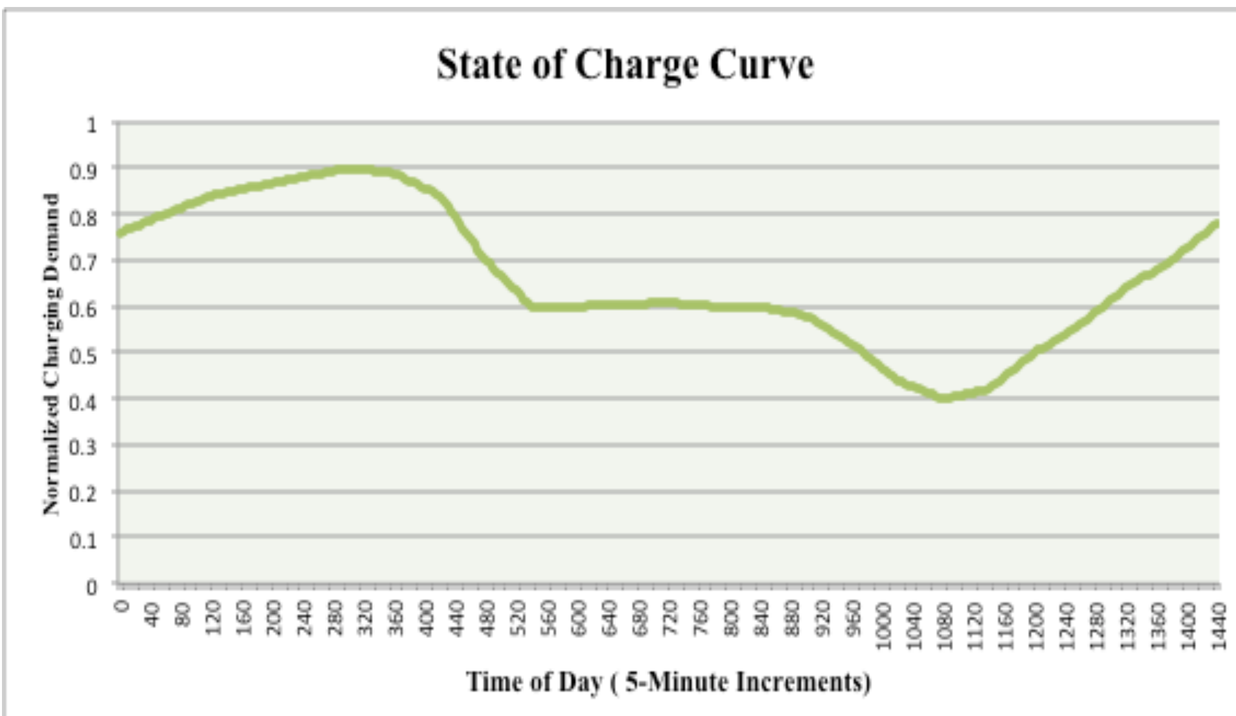

Figure 2.4 SOC Curve

To keep the SOC demand greater than 0.4 (40%) we multiplied the normalized charging demand curve by 0.6 then subtracted it from 1 to get the SOC demand estimation as given in (1).

$$\boldsymbol{SOC\ demand = 1 - .6 * (Charging\ Demand/\ Peak\ Demand)} \quad \textbf{(1)}$$

In order to make the SOC demand respond to the charging done at each time step, we developed the equation as given in (2).

$$\boldsymbol{SOC(i) = SOC\ demand(i) + \frac{P\_charging(i-1) * Station\ MW * \left(\frac{1}{12}\right)}{Station\ Capacity}} \quad \textbf{(2)}$$

The SOC is defined in per-unit (p.u) value indicating the composite energy level for the EVs at the charging station. In Eq.2, P-charging is the pu. power absorbed by the vehicles at the station (the output of the controllers). Station MW is the power rating of the V2G station, Station Capacity is the V2G station capacity in MW/h and 1/12 is a scaling factor related to the 5-minute time step used.

Chapter 3 - Engineering Problem and Research Plan

3.1 Engineering Problem

In order to focus the investigation, a series of research questions and hypotheses were developed. Each question aids in developing a systematic method to determine the critical performance metrics of a V2G enabled power system stability. They are listed below with no particular priority placed on their order.

- Research Questions:
    1. Is Vehicle to Grid (V2G) a valid technology to achieve or help with the voltage stability of the electric power grid?
    2. What form should the fuzzy logic V2G controller take?
- Outcome of the proposed research:
    1. Simulation of V2G system with fuzzy logic V2G controller
    2. Comparison of logic schemes
    3. Investigation of effect of charger location and voltage sensitivity
    4. Investigation of effect of VAR injection vs. real power injection

3.2 Research Plan

The first approach to accomplish our research goals for this thesis is to understand the concepts of EV integration into the grid system from the aspect of helping with the voltage stability of the system. The features of the battery of the EV are used to help assume and set the V2G station state-of-charge. This thesis utilizes two test power systems (16 generator system and 6 generator system) [19, 20]. The two test systems are studied to analyze the limitations of the grid. An outline of the thesis was created to put things into perspective:

1. Simulate a power system using a load flow analysis, following a daily load curve.
    1.1. Set up a Matlab based simulation to run repeated load flow calculations.
    1.2. Develop a load curve based on the central Florida data set, and scale the data for each of the two test systems.
    1.3. Modify load flow data for the loads according to the load curve.
    1.4. Set up a loop to step through the day in 5-minute steps.
2. Add the Vehicle to Grid system into the simulation.
    2.1. Develop a SOC curve estimated from the charging demand in the Nordic Region to achieve a normalized SOC demand curve to use in this thesis.
    2.2. Scale the data for each of the two test systems.
    2.3. Develop a station SOC equation utilizing the SOC demand curve (Eq.2).
3. Design and test five Fuzzy logic controllers to examine the effects of each controller on the system in regards to voltage stability:
    3.1. Standard On/off Controller modeled in the fuzzy framework
    3.2. Best Fuzzy Controller
    3.3. Voltage Dependent Controller
    3.4. Grid Dependent Controller
    3.5. Balanced Controller

4. Determine the weak buses and strong buses with regard to voltage stability in both of our test systems in order to select the ideal place for the charging station.
5. Investigate the possibility of discharging using Q (Vars) to determine if it helps even more than discharging P (real) power to the grid.

Chapter 4 - Analysis and Research Results

4.1 Introduction of the different Test System

In order to introduce the V2G application, the test systems used are introduced.

4.1.1 16-Generator System

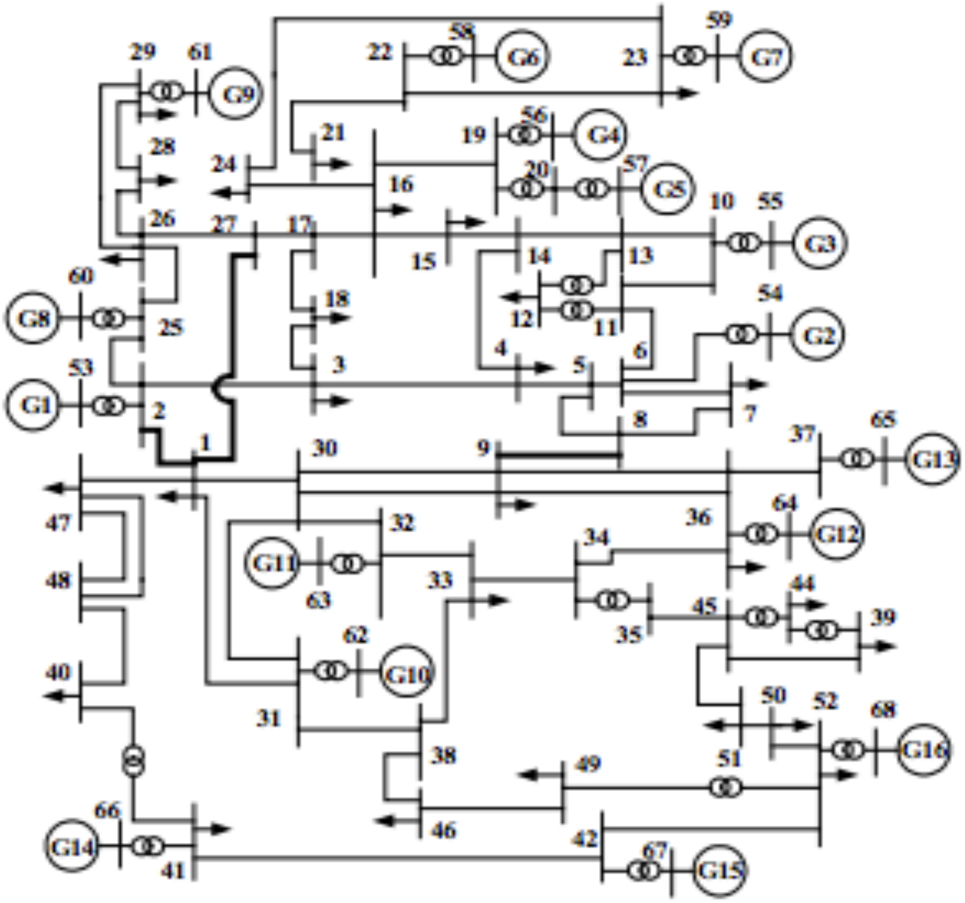

Figure 4.1 16-generator 68 bus test system [19]

Fig. 4.1 shows a single line diagram of 16-generator 68-bus test system, which is a reduced order of the New England test system interconnected with the New York Power system [19]. This system has been used by many researchers for impact studies of new controllers for power system stability [19]. The V2G stations are located at Bus 49 (weak bus) and Bus 4 (strong bus). V2G stations were modeled as PQ loads in load flow simulations, using the Cherry Tree Power System toolbox for Matlab [20].

4.1.2 6- Generator System

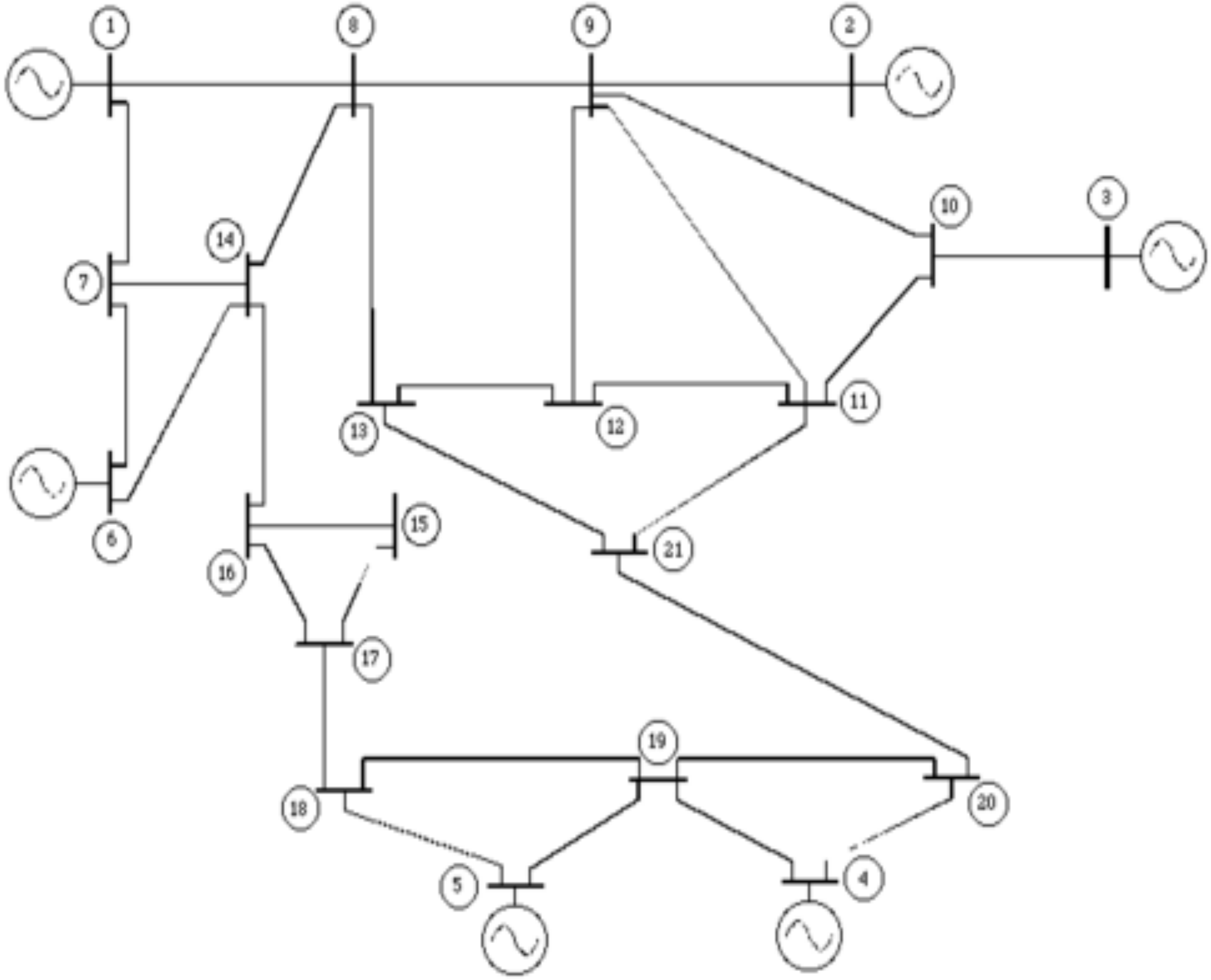

Figure 4.2 6-generator 21 bus test system [21]

Fig. 4.2 shows a single line diagram of 6-generator, 21-bus test system [20, 21]. This test system includes 21 busses, 6 generators, and 30 lines. The slack bus is located at Bus 16. The V2G stations are located at Bus 9 (weak bus) and Bus 1 (strong bus) [20]. Again V2G stations were modeled as PQ loads in load flow analysis.

4.2 Fuzzy Logic Controller in V2G Framework

Uncoordinated charging or discharging of EV's can interrupt the voltage profile at the nodes. For example, an uncontrolled charge or discharge rate of the EVs' power may cause the node voltages to increase or decrease past the standard norms. In this thesis, the charging and discharging rates have been controlled by using a fuzzy logic controller. For example, the input parameters to the charging station controller are taken as the current combined vehicles' SOC at a charging station and the voltage level at the node on which the charging station is located. For a low SOC and high node voltage, the EV will charge, while for a high SOC and low node voltage, the EV will discharge. However, there may also be cases where both the SOC and node voltages are both high or both are low. For such situations, a limited charging or discharging rate needs to be implemented. Thus, the Fuzzy Logic Controllers have been modified to take care of such situations as well, so as to try to keep the node voltage variations within the specified norms. Each controller utilizes different rules to favor either the SOC or the voltage level to different degrees.

4.3 Base Case Analyses

4.3.1 Fuzzy Logic Variables

In this thesis two conflicting needs are considered. On one hand, the grid's voltage stability must be maintained. On the other hand, the vehicles' batteries must be charged. Thus we utilized two input variables to represent these needs. Voltage magnitude at the charger bus is utilized to represent system voltage health or status. State of charge used to indicate an overall battery charge level for a V2G charging station. Voltage input variable is divided into five membership functions, namely, Very Low (VL), Low (L), Medium (M), High (H), Very High (VH). The SOC of the station is divided into five membership functions, Very Low (VL), Low

(L), Medium (M), High (H), and Very High (VH). Every one of these variables will form a fuzzy set.

The charging and discharging rates are divided into seven levels (very negative < medium negative < small negative < zero < small positive < medium positive < very positive). Observe that each charge rate level is assigned a specific charge rate value according to the Suguno and inference scheme (see Table 5.1).

Discharging   Charging

VN	MN	SN	Z	SP	MP	VP
-0.96	**-0.66**	**-.33**	**0**	**0.33**	**0.66**	**0.96**

Table 4.1 Fuzzy Logic Controller Charging Rate

4.3.2 Fuzzy Logic Rule Base

Table 4.2 gives a simple rule base for a fuzzy V2G controller. Because there are five membership functions for each input, 25 rules are need, and are shown in the table.

Looking at Table 4.2, column 3 and row 3, one rule in the fuzzy logic controller can be expressed as follows:

"IF the SOC of the Electrical Vehicle is at LOW level, and the grid Voltage is LOW, THEN the discharging rate should be Small Positive (SP)."

SOC / V	VL	L	M	H	VH
VL	MP	SP	Z	MN	VN
L	MP	**SP**	Z	SN	MN
M	VP	MP	SP	Z	SN
H	VP	MP	SP	SP	Z
VH	VP	VP	MP	SP	Z

Table 4.2 Sample Fuzzy Logic Controller Rule Set

Thus, if the EVs' are not fully charged, but the low voltage indicates the system is weak, the charging rate is minimal (favoring the EVs slightly more than the system).

These control rules are based on the knowledge of power stability and the relation between SOC of the Electric Vehicles and Voltage level of the Grid. It can be further explained in three aspects.

- The lower the voltage of the grid, the weaker the system is, and the higher the discharging rates should be.
- The higher the voltage of the grid is, the stronger the system is, and the higher the charging rates should be.
- The higher the SOC of the EVs is, the higher power it can output and the lower power it needs to take.

By establishing such fuzzy control rules, the actions and outputs of the system follow the knowledge created. Therefore, as long as the knowledge about the application is correct, the outputs can be acceptable. Furthermore, while the mathematical models of the grid and the State of Charge of the Electric Vehicle are too complex to develop, fuzzy control rules can drive the system to work as wanted, without getting into mathematical details and vast calculations. Consequently, a control plan is needed even if it cannot always grant us the best outcome with high accuracy. This is also extremely difficult to achieve by attempting to establish the mathematical models of batteries and the grid since they depend on many unpredictable factors and the parameters vary all the time.

4.3.3 Case 1: Standard Fuzzy Controller

In the first case, we have designed and tested what we called the Standard Fuzzy Controller. This standard fuzzy controller can be explained easily as a fuzzy implementation of a standard ON/OFF controller, which means that there are no smart rules or conditions implemented to help either the grid or the EVs. The EVs simply charge until they are full.

Looking at Table 4.3, we see that no matter how the grid is in need of help, it is still instructed to charge the electric vehicle, and hence not help with voltage stability. As long as the SOC is not VH (fully charged) the controller keeps drawing power at the highest level (output is VP). For example, if we read the fuzzy controller rule in column 2, row 2:

*"IF the SOC of the Electrical Vehicles is at **Very Low** level, and the grid Voltage is **Very Low**, THEN the charging rate should be Very Positive (VP)."*

V \ SOC	**VL**	**L**	**M**	**H**	**VH**
VL	VP	VP	VP	VP	Z
L	VP	VP	VP	VP	Z
M	VP	VP	VP	VP	Z
H	VP	VP	VP	VP	Z
VH	VP	VP	VP	VP	Z

Table 4.3 Standard Fuzzy Controller

A series of graphs Figs. 4.3-4.6 follows to further explain how this controller performs in regards to voltage stability in both the 16 and the 6-generator systems, as compared to no charger present.

4.3.3.1 Standard Controller, 16-Generator System, V2G station at Bus 49

Fig. 4.3 shows the voltage magnitude at Bus 49 of the 16-generator system as a function of time of day for the Standard Controller (P= Fuzzy) and for the case of no controller (P=0). As the simulation progresses the load increases to a maximum at around minute 1050 (5:30pm). The voltage dips to 0.8732 pu. and increases as high as 1.07 pu. This is slightly lower than the case without V2G because of the added load flow of the charger.

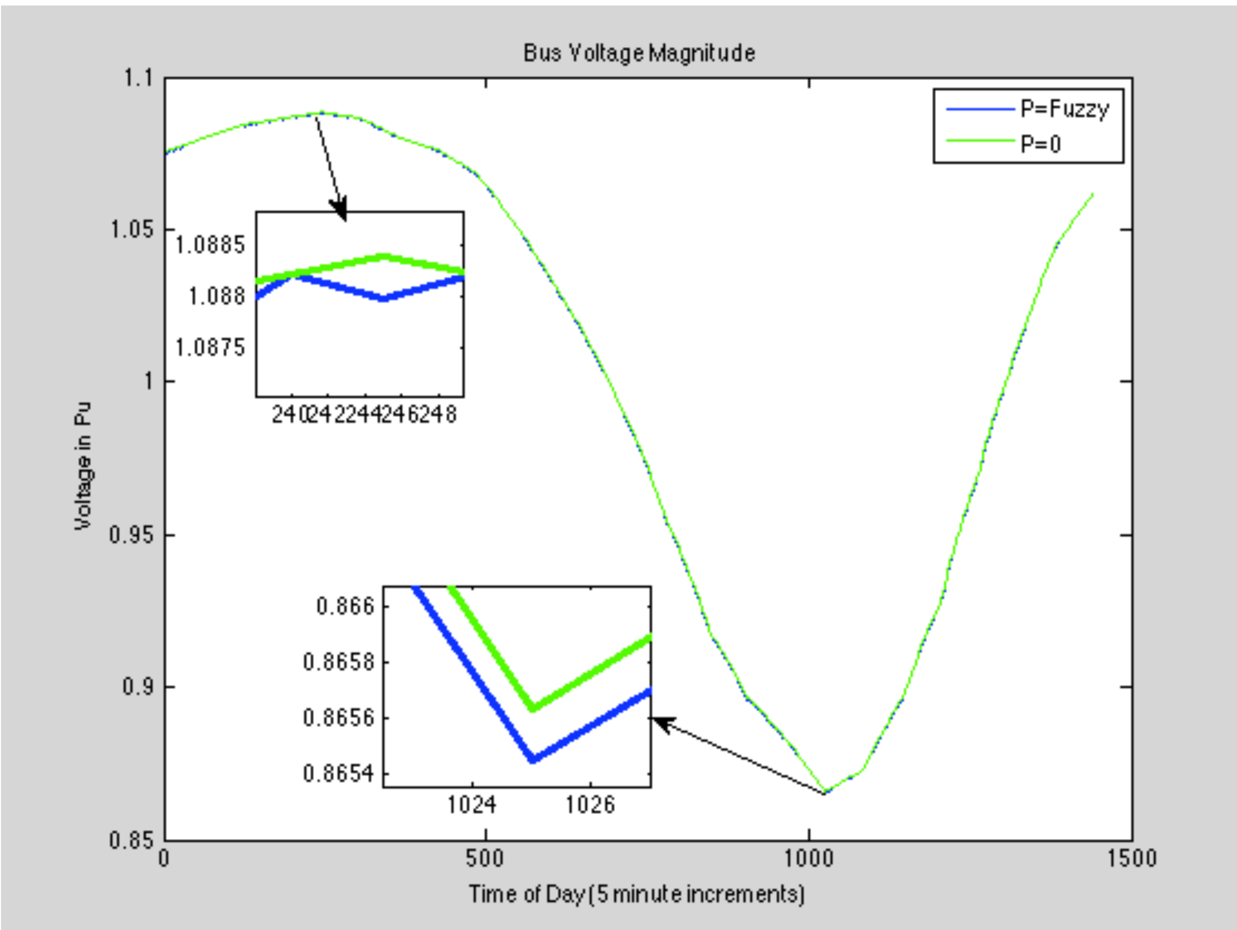

Figure 4.3 Standard Fuzzy Controller (Voltage) at Bus 49, 16-gen

Figure 4.4 shows the SOC of the charger. The basic shape follows the aggregated SOC curve built from the reference data, with the chargers actually working to increase the SOC. Note that when the SOC is greater than 0.75 pu the charging rate is such that the SOC goes over 1 within the 5-minute time step. This causes the charger not to charge in the next time step, causing the saw tooth pattern. This is an anomaly of choosing a 5-minute step time for the simulation, and the fast charging rate allowed for the Standard Charger.

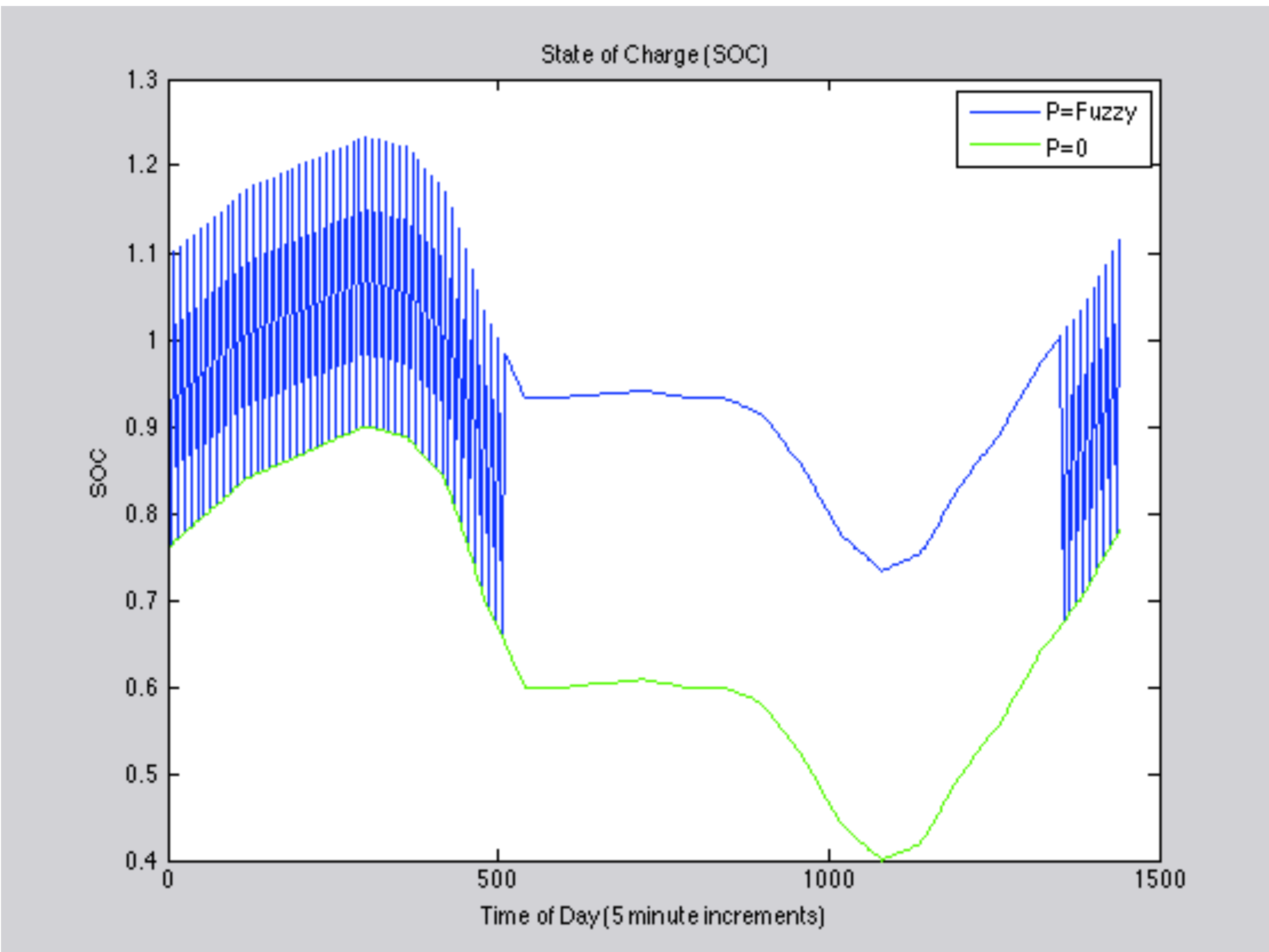

Figure 4.4 Standard Fuzzy Controller (SOC) at Bus 49, 16-gen

4.3.3.2 Standard Controller, 6-Generator System, V2G station at Bus 9

Figure 4.5 shows the voltage magnitude at Bus 9 of the 6-generator system as a function of time of day for the Standard Controller (P= Fuzzy) and for the case of no charger (P=0). As we can see that the voltage is low with the V2G falling less than 0.8 pu.

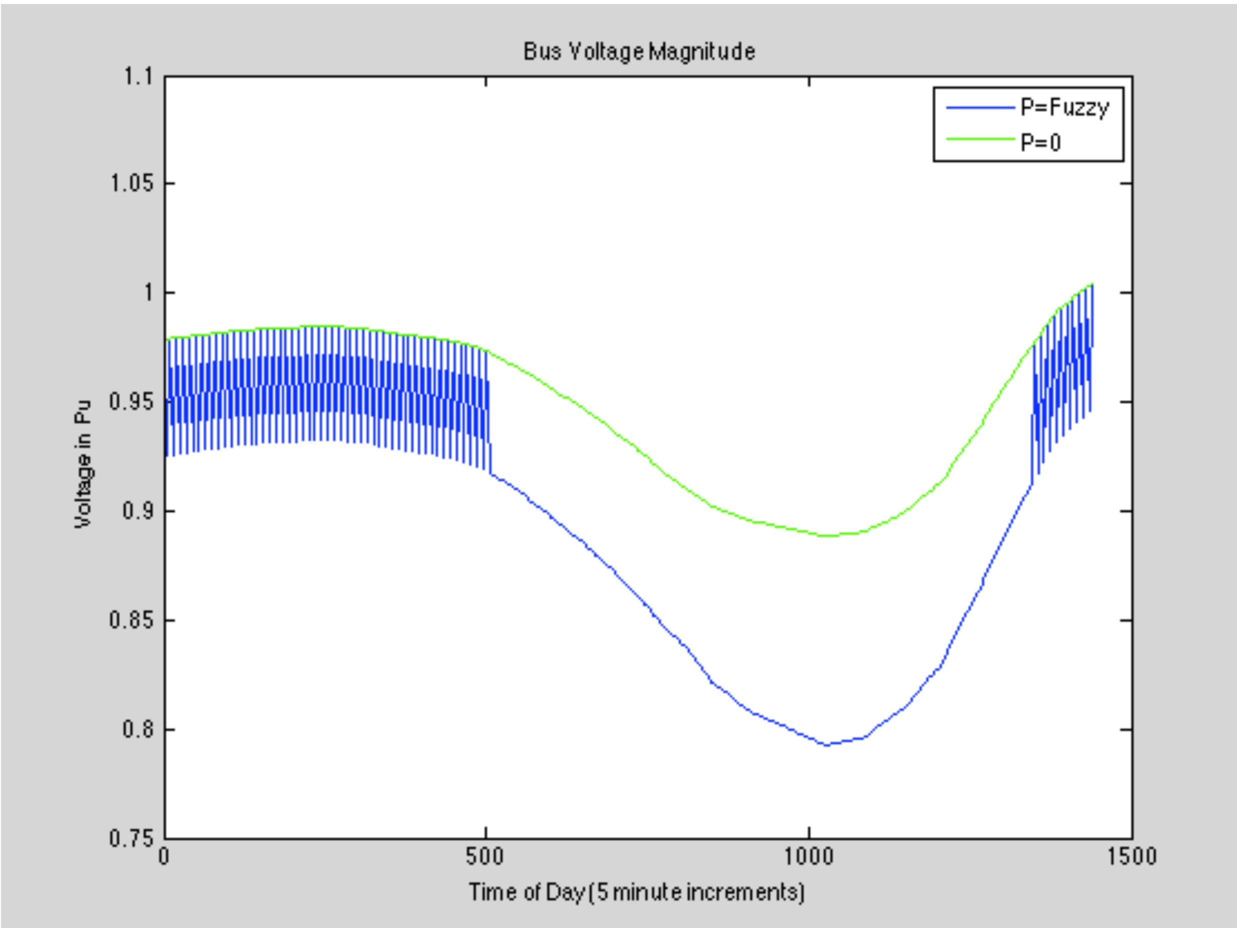

Figure 4.5 Standard Fuzzy Controller (Voltage) at Bus 9, 6-gen

Figure 4.6 shows the SOC of the station. The basic shape follows the aggregated SOC demand curve built from the reference data [29], with the chargers actually working to increase the SOC. Again the saw tooth pattern is evident due to the fast charging and time step, similar to Fig. 4.4.

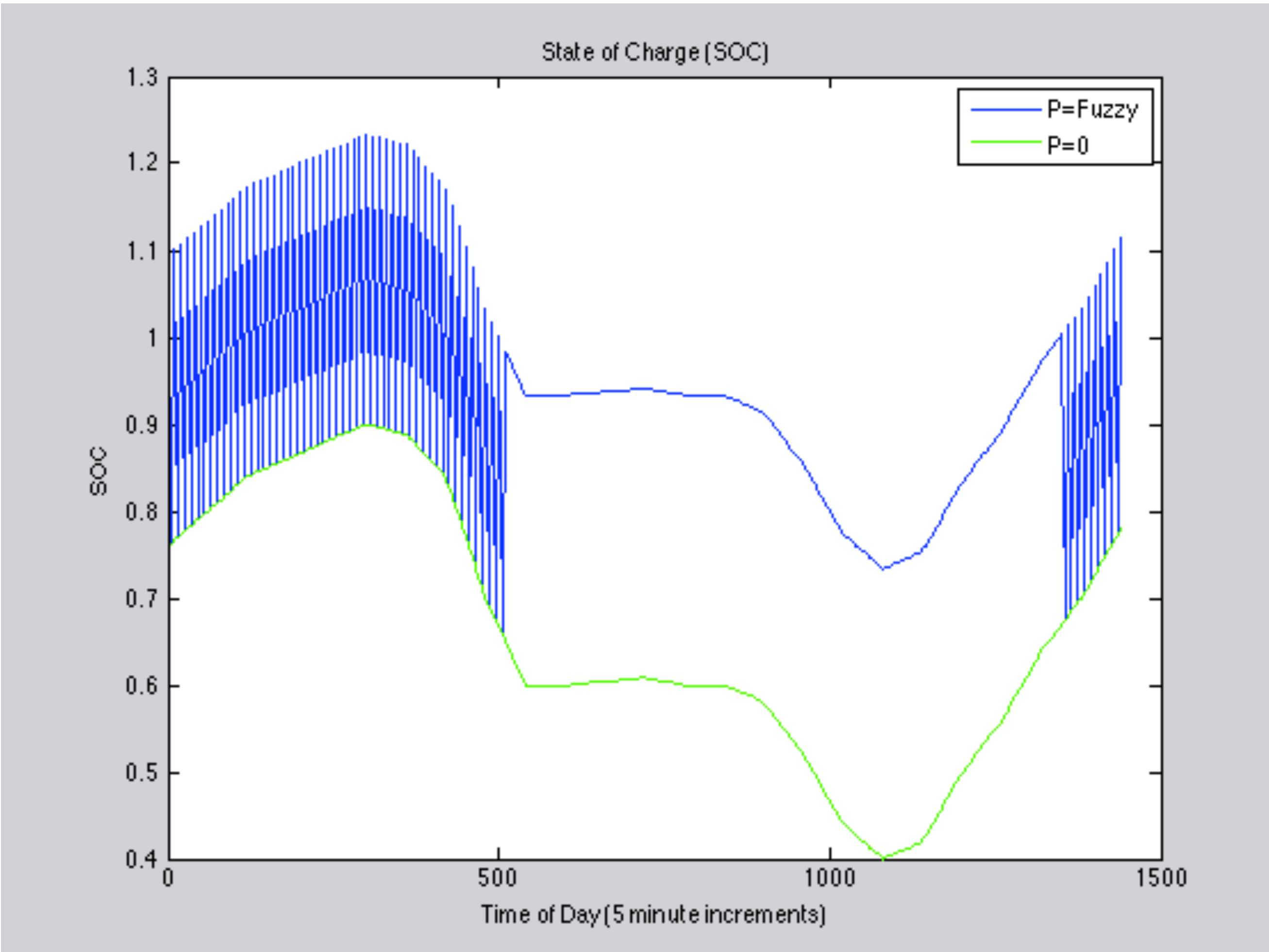

Figure 4.6 Standard Fuzzy Controller (SOC) at Bus 9, 6-gen

4.3.4 Case 2: Best Fuzzy Controller

In this case a Best Fuzzy Controller is designed. The Best Fuzzy Controller is the most balanced and smart fuzzy designed in this thesis based on the literature review [27, 3, 18]. This controller balances the needs of charging and voltage between the grid and the electric vehicles.

Looking at Table 4.4, we see that both SOC of the Electric Vehicle and voltage of the grid needs are balanced. Although this controller favors charging a bit more than voltage stability compared to Case 5 (Table 4.7). For example, even if the voltage is Very Low (Row 2 of Table 4.) the controller still charges for SOC Very Low and Low.

V \ SOC	VL	L	M	H	VH
VL	MP	SP	Z	MN	VN
L	MP	SP	Z	SN	MN
M	VP	MP	SP	Z	SN
H	VP	MP	SP	SP	Z
VH	VP	VP	MP	SP	Z

Table 4.4 Best Fuzzy Controller

A series of graphs, Figs. 4.7-4.10, follows to further explain how this controller performs in regards voltage stability in both the 16 and the 6-generator systems. Again a simulation with no V2G station present is included on each graph for comparison purposes.

4.3.4.1 Best Controller, 16-Generator System, V2G station at Bus 49

Fig. 4.7 shows the voltage magnitudes at Bus 49 of the 16-gernerator system as a function of time of day for the Best Controller (P=Fuzzy) and no V2G station (P=0). The voltage profile is largely unchanged.

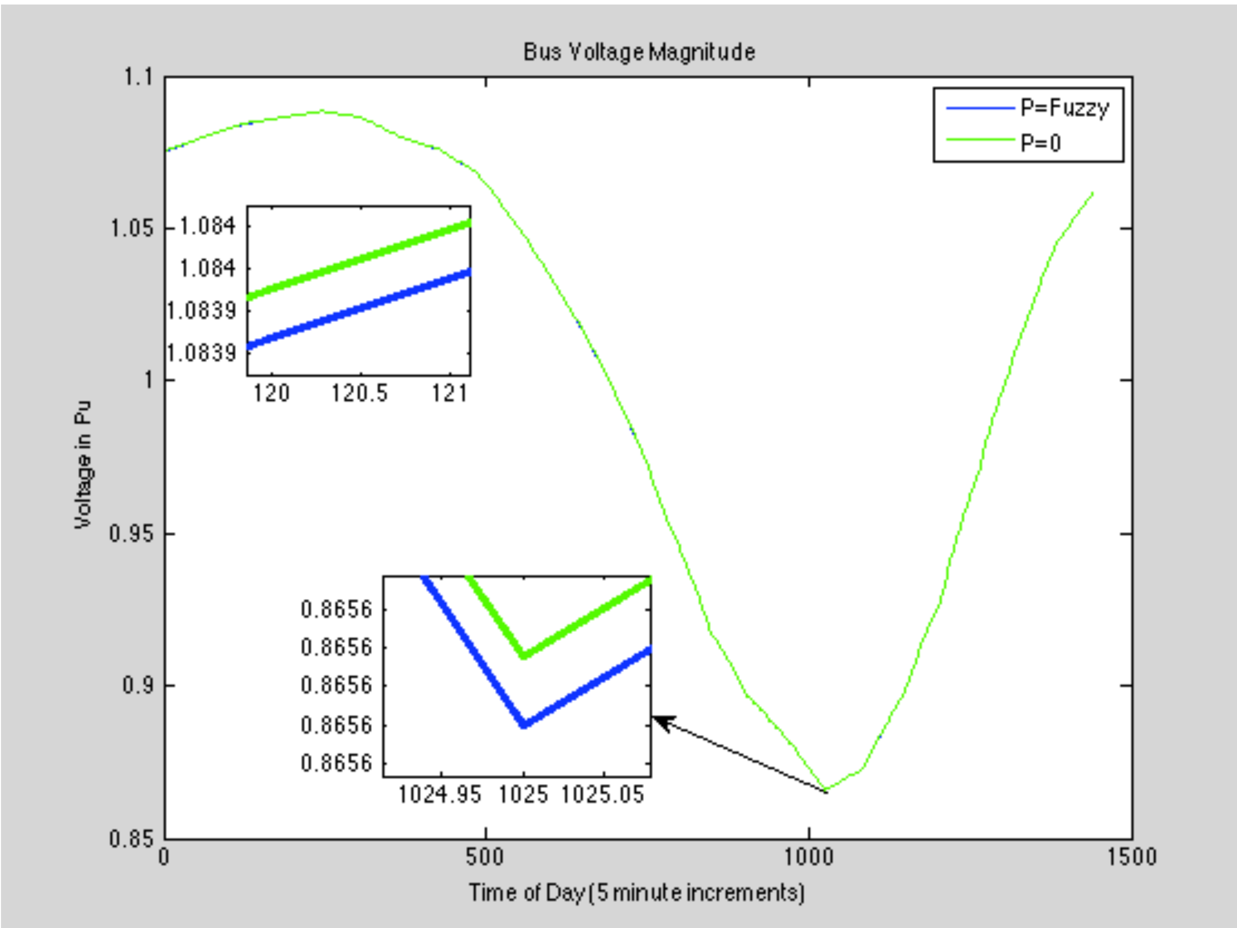

Figure 4.7 Best Fuzzy Controller (Voltage) at Bus 49, 16-gen

Fig. 4.8 shows the SOC of the charger. The basic shape follows the aggregated SOC demand curve built from the reference data [18]. The SOC is significantly reduced compared to the results seen for the Standard Controller. Note the time period from approximately 800-1000 minutes when the SOC is lower than the SOC demand, indicating that the V2G system is providing power to the system to help improve the voltage profile.

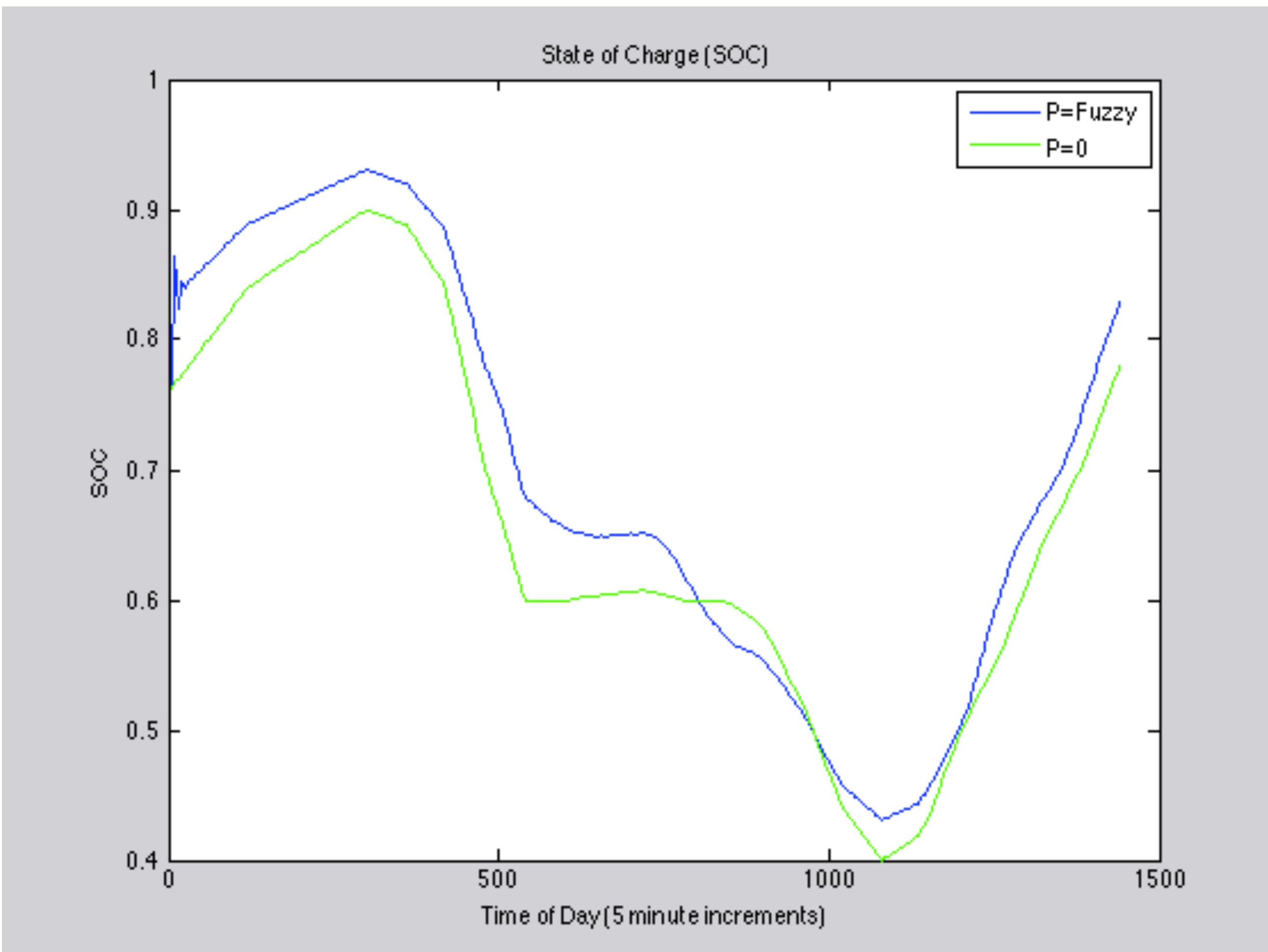

Figure 4.8 Best Fuzzy Controller (SOC) at Bus 49, 16-gen

4.3.4.2 Best Controller, 6-Generator System, V2G at Bus 9

Fig. 4.9 shows the voltage magnitudes at Bus 9 of the 6-generator system for the Best Controller case as a function of time of day. The voltage profile is much less affected by the presence of the charger than in corresponding Standard Controller case (Fig. 4.9), but there are still periods (approximately 950 to 1200 minutes) where the V2G system adversely affected the bus voltage.

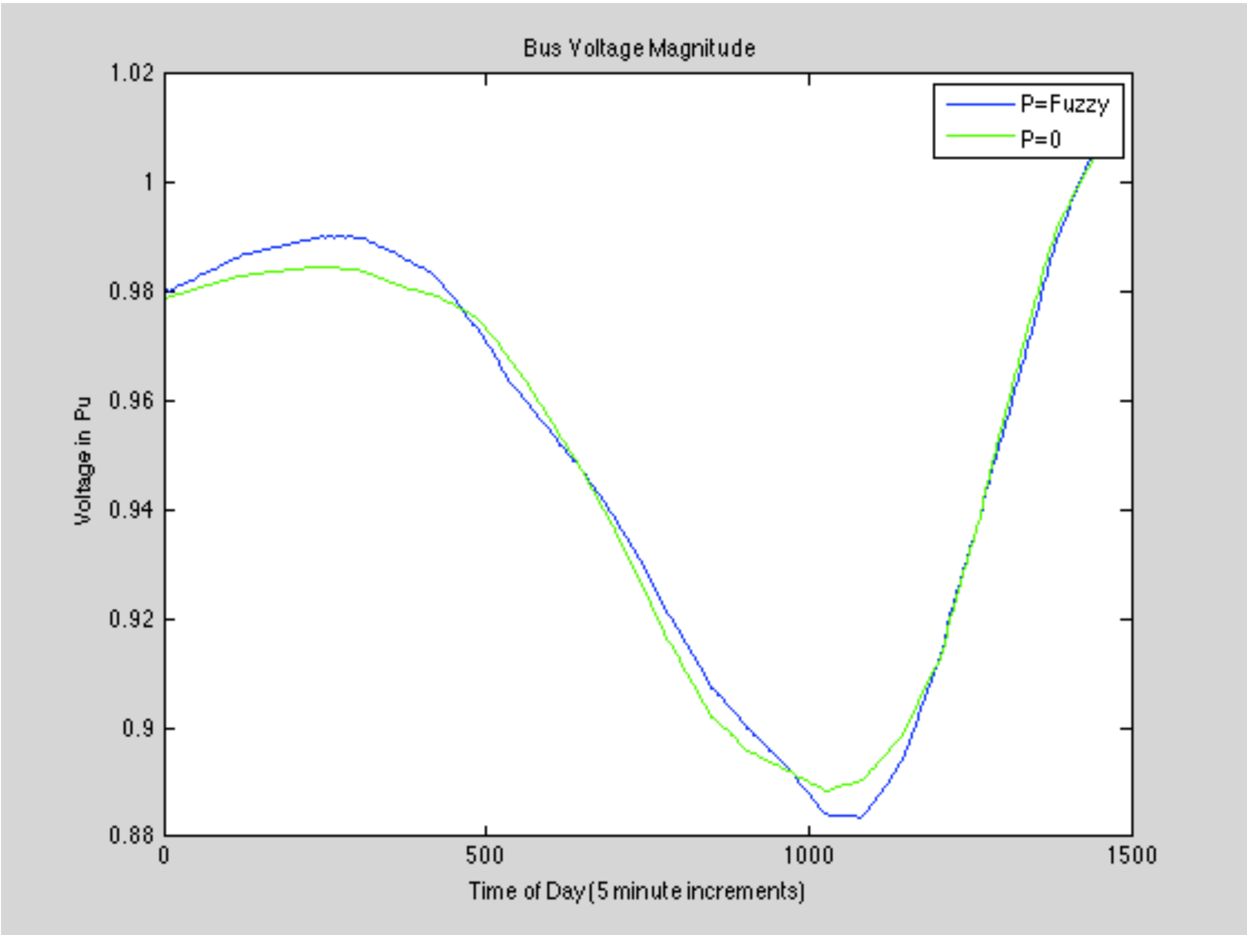

Figure 4.9 Best Fuzzy Controller (Voltage) at Bus 9, 6-gen

Fig. 4.10 shows the SOC of the charger for this case. The SOC is significantly reduced compared to the Standard fuzzy controller for this case (Fig. 10). Again we can see that for several periods the V2G is discharging, as indicated by the Fuzzy Controller curve being below the no charger (P=0) curve.

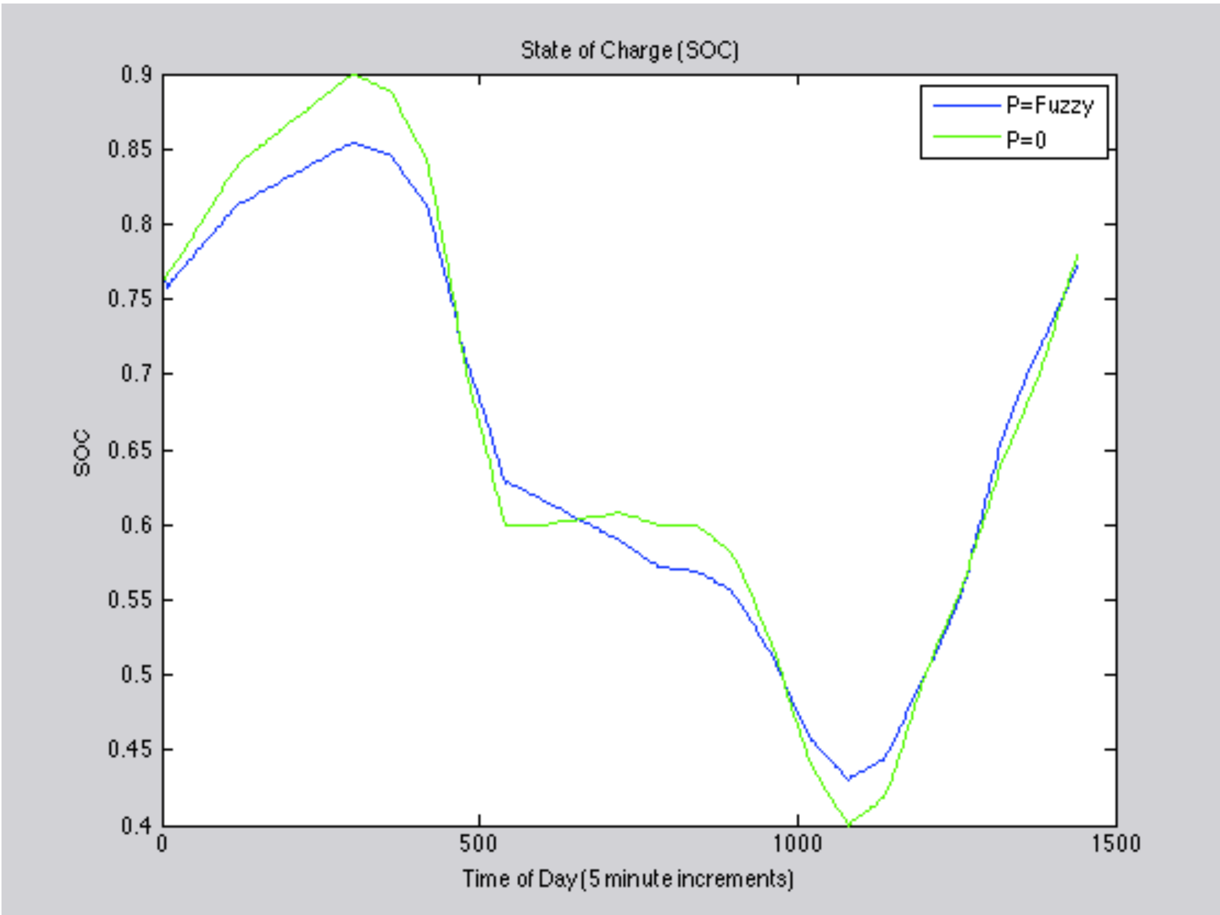

Figure 4.10 Best Fuzzy Controller (SOC) at Bus 9, 6-gen

4.3.5 Case 3 SOC Dependent Controller

In Case 3, a SOC Dependent Controller is designed and tested. The SOC Dependent Fuzzy Controller is designed in this thesis to see the effect of a controller depending only on the SOC of the EV batteries.

Looking at Table 4.5, we see that no matter what the level of the grid's voltage, it is instructed to keep charging until the SOC is High and in return the Electrical Vehicle is only discharging (with SN) when the SOC is at Very High level.

SOC / V	VL	L	M	H	VH
VL	VP	MP	SP	Z	SN
L	VP	MP	SP	Z	SN
M	VP	MP	SP	Z	SN
H	VP	MP	SP	Z	SN
VH	VP	MP	SP	Z	SN

Table 4.5 SOC Dependent Fuzzy Controller

Figs. 4.11-4.14 follow to further explain how this controller compares to the no charger case in both the 16 and the 6-generator systems.

4.3.5.1 SOC Dependent Controller, 16-Generator System, V2G at Bus 49

Fig. 4.11 shows the voltage magnitude at Bus 49 of the 16-generator system for the SOC dependent controller for the 16-generator system. The voltage profile is largely unchanged by the presence of the V2G system.

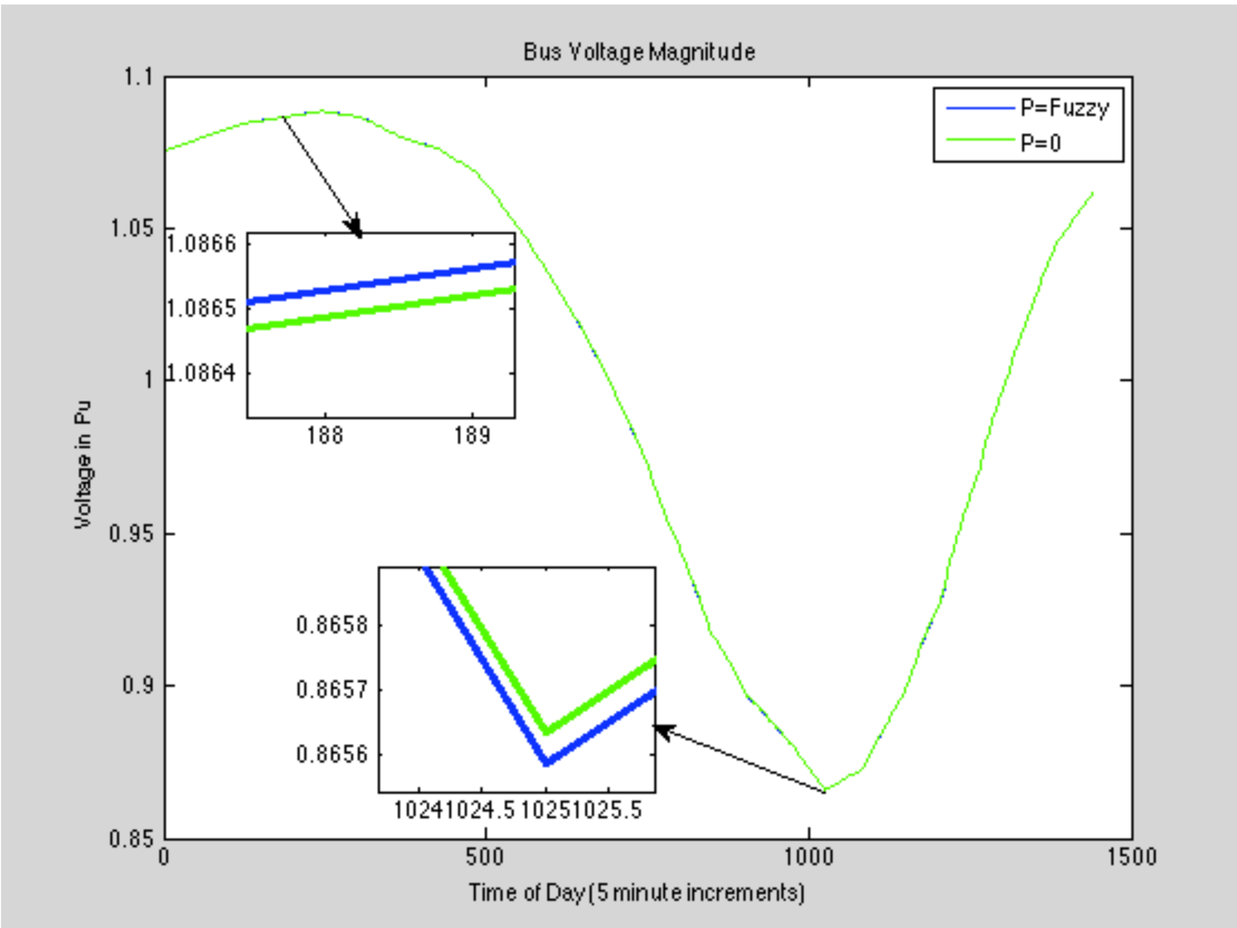

Figure 4.11 SOC Dependent Fuzzy Controller (Vloads) at Bus 49, 16-gen

Fig. 4.12 shows the SOC of the station compared to the no-charger case. Note that early in the day when the SOC is high, the charger discharges (as indicated by the Fuzzy SOC curve by lower than the P=0 case).

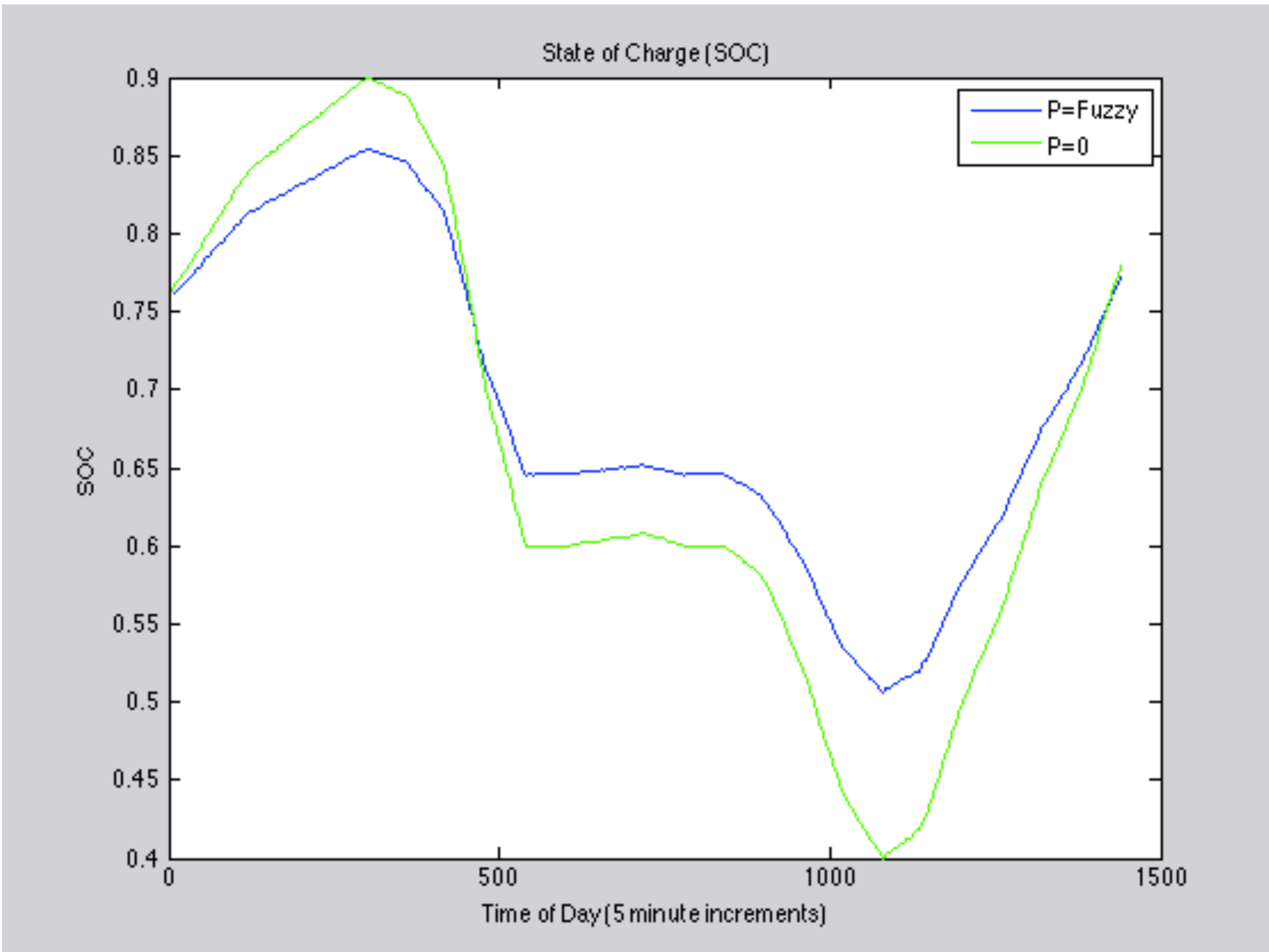

Figure 4.12 SOC Dependent Fuzzy Controller (SOC) at Bus 49, 16-gen

4.3.5.2 SOC Dependent Controller, 6-Generator System, V2G at Bus 9

Fig. 4.13 shows the voltage magnitudes at Bus 9 for the 6-generator system as a function of time of day. This controller degrades the bus voltage when the load is high (mid day).

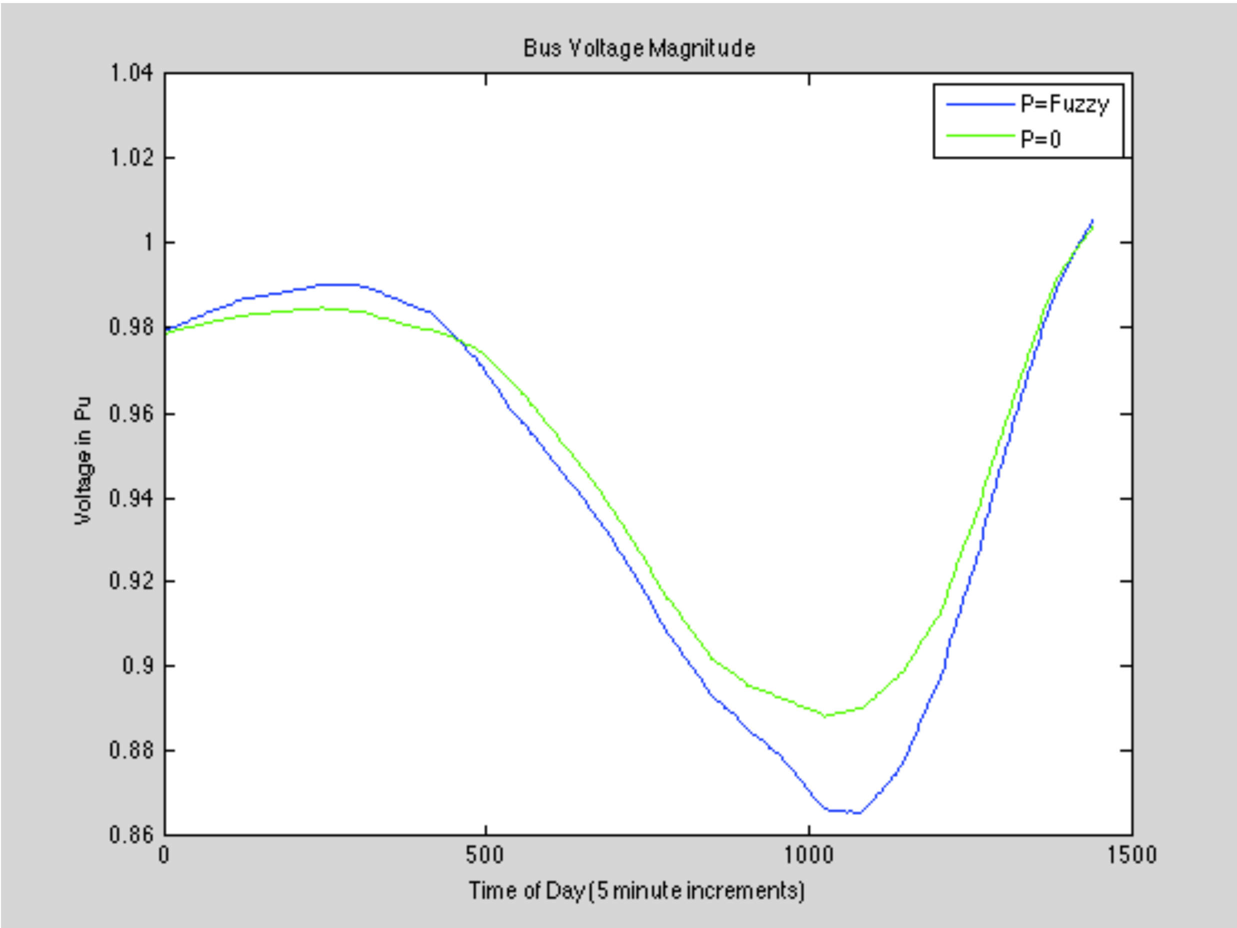

Figure 4.13 SOC Dependent Fuzzy Controller (Voltage) at Bus 9, 6-gen

Fig. 4.14 shows the SOC of the charger for the SOC dependent V2G station. We see significant charging when the SOC is low.

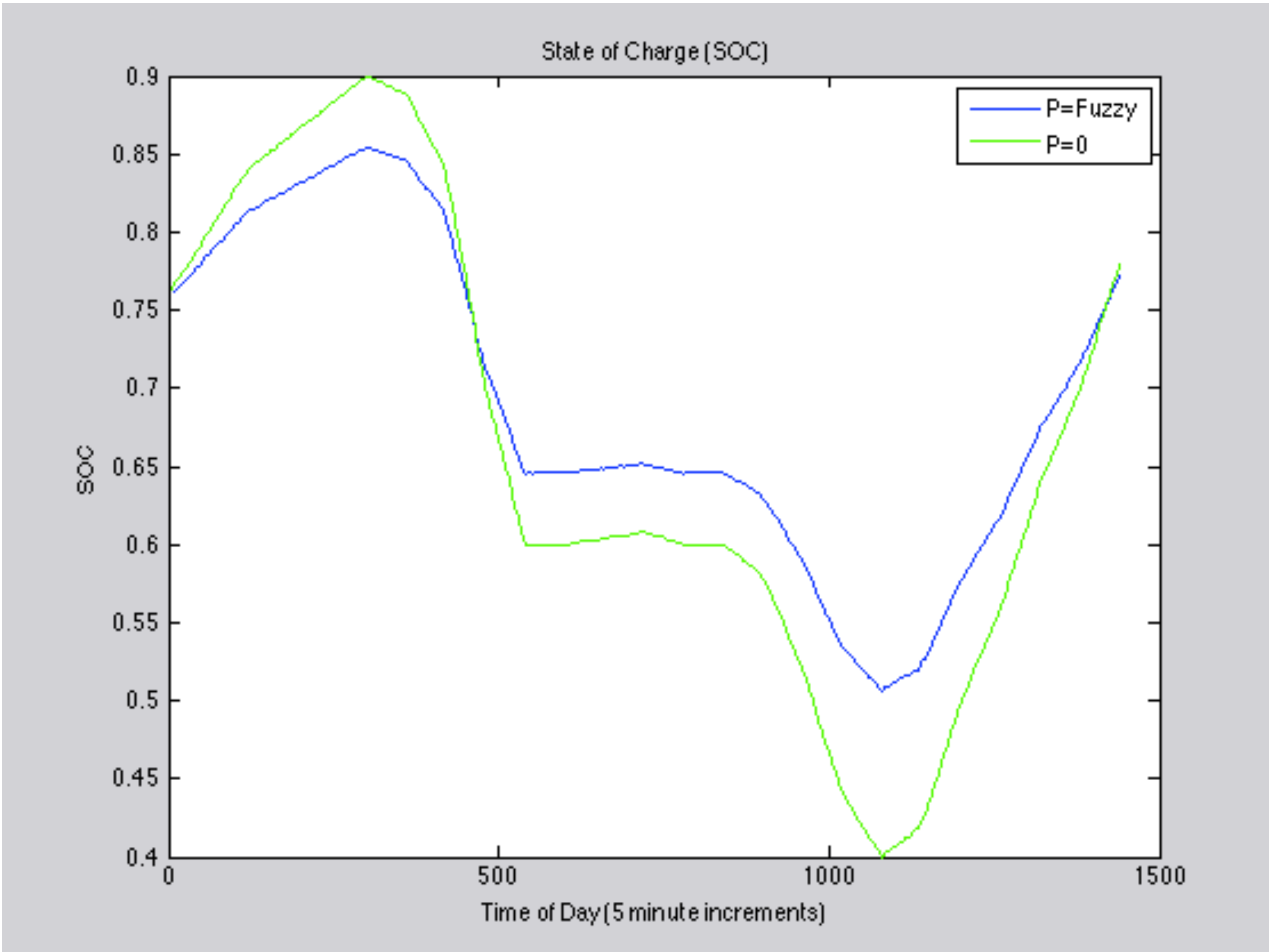

Figure 4.14 SOC Dependent Fuzzy Controller (SOC) at Bus 9, 6 gen

4.3.6 Case 4 Voltage Dependent Controller

In the fourth case a Fuzzy Controller is designed and tested and called the Voltage Dependent Controller. In this case the controller is depending only on the bus voltage. This controller is designed to allow us to see how much the controller will help the voltage stability.

Looking at Table 4.6, we see that the controller output is mainly negative (discharging) until the voltage level High or Very High, independent of V2G SOC.

V \ SOC	**VL**	**L**	**M**	**H**	**VH**
VL	VN	VN	VN	VN	VN
L	MN	MN	MN	MN	MN
M	SN	SN	SN	SN	SN
H	SP	SP	SP	SP	SP
VH	VP	VP	VP	VP	VP

Table 4.6 Voltage Dependent Fuzzy Controller

In this case a series of graphs (Figs. 4.15-4.18) follows to further explain how this controller is performing in regards voltage stability in both the 16 and the 6-generator systems.

4.3.6.1 Voltage Dependent Controller, 16-Generator System, V2G at Bus 49

Fig. 4.15 shows the voltage magnitude at Bus 49 of the 16-generator system as a function of time of day. The voltage profile is largely unchanged.

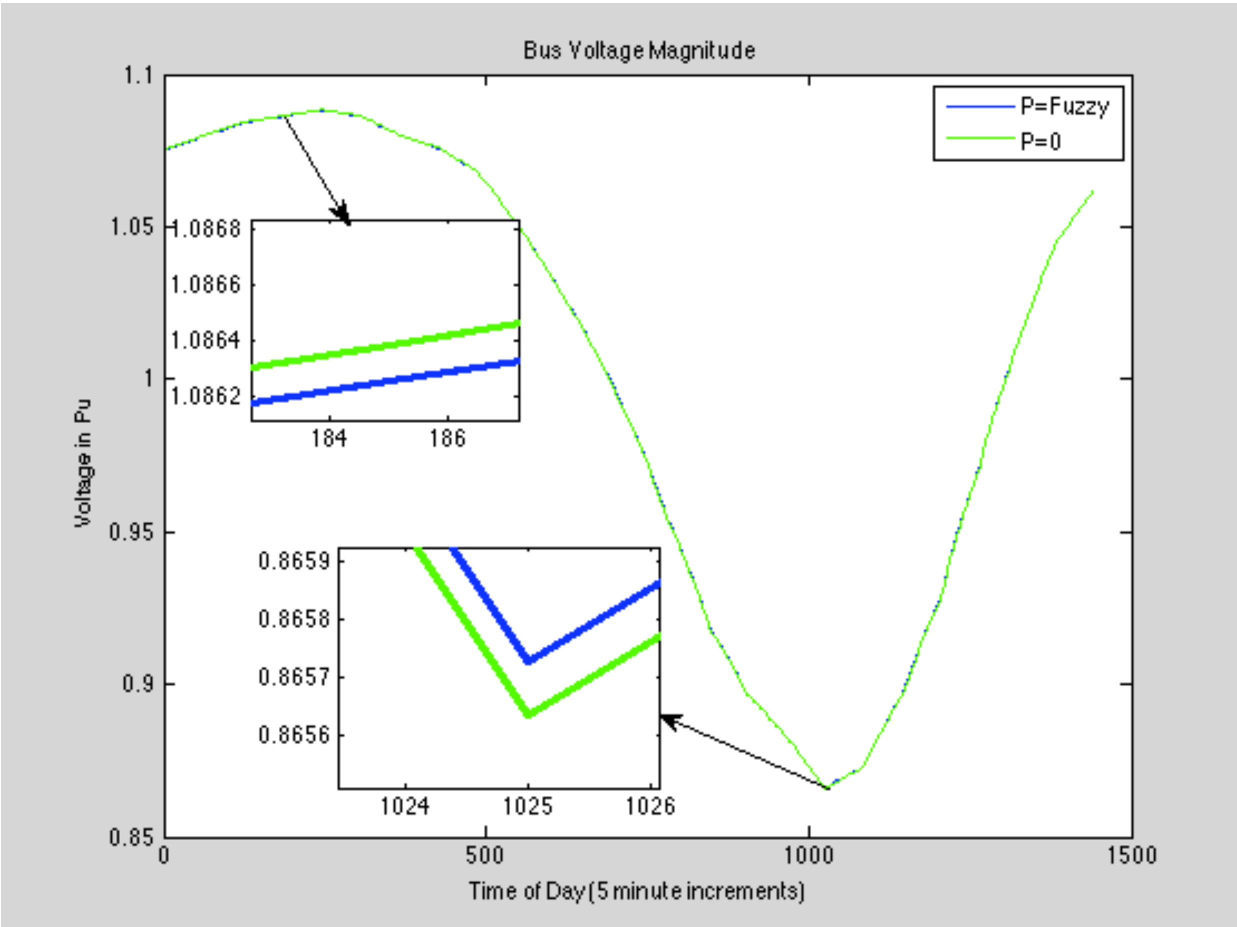

Figure 4.15 Voltage Dependent Fuzzy Controller (Voltage) at Bus 49, 16-gen

Fig. 4.16 shows the SOC of the charger. This controller's SOC curve is below the no charger curve for much of the day, indicating its discharging effects.

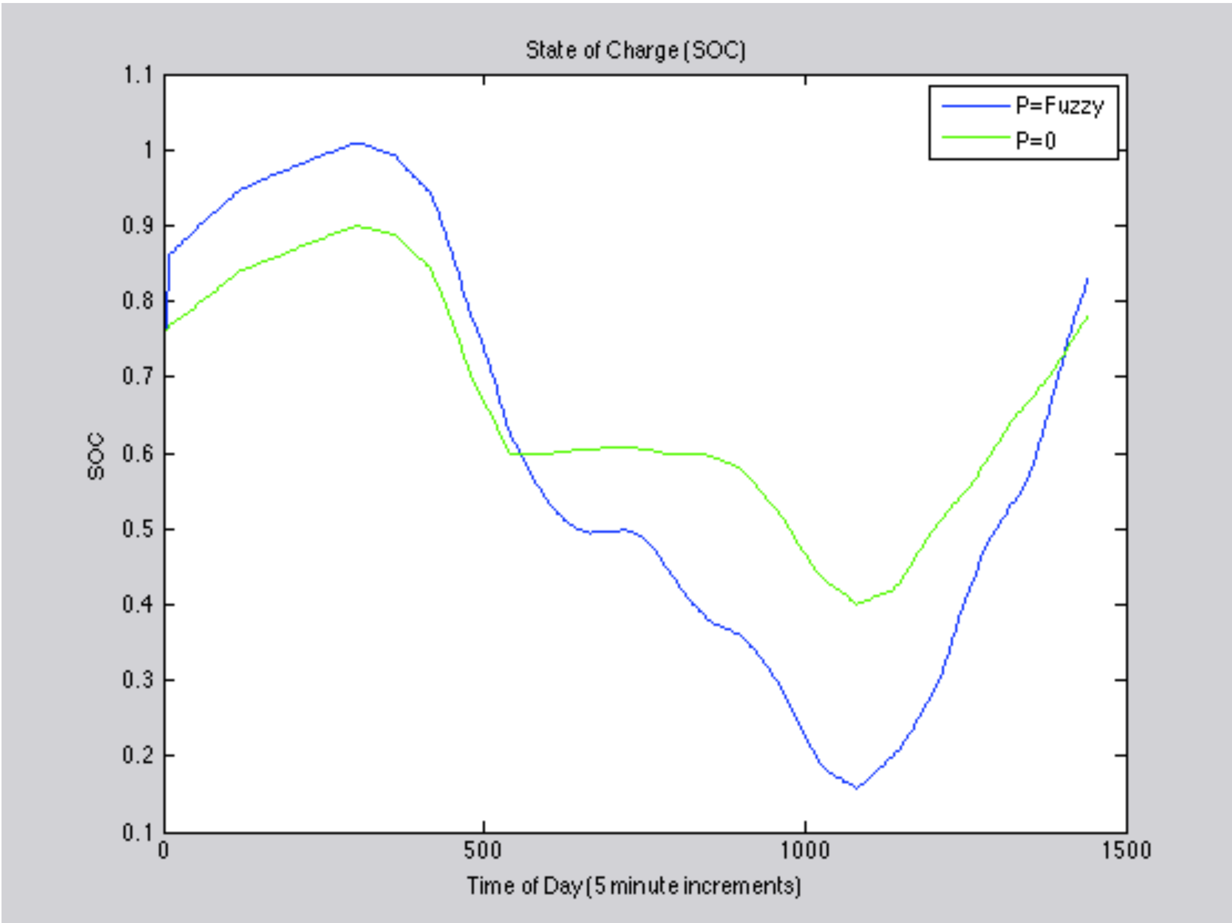

Figure 4.16 Voltage Dependent Fuzzy Controller (SOC) at Bus 49, 16-gen

4.3.6 2 Voltage Dependent Controller, 6-Generator System, V2G at Bus 9

Fig. 4.17 shows the Voltage dependent controller case's voltage magnitude at Bus 9 of the 6-generator system as a function of time of day. The voltage profile is significantly improved by the presence of the V2G. We can observe that the V2G helping out by reducing the load on the system.

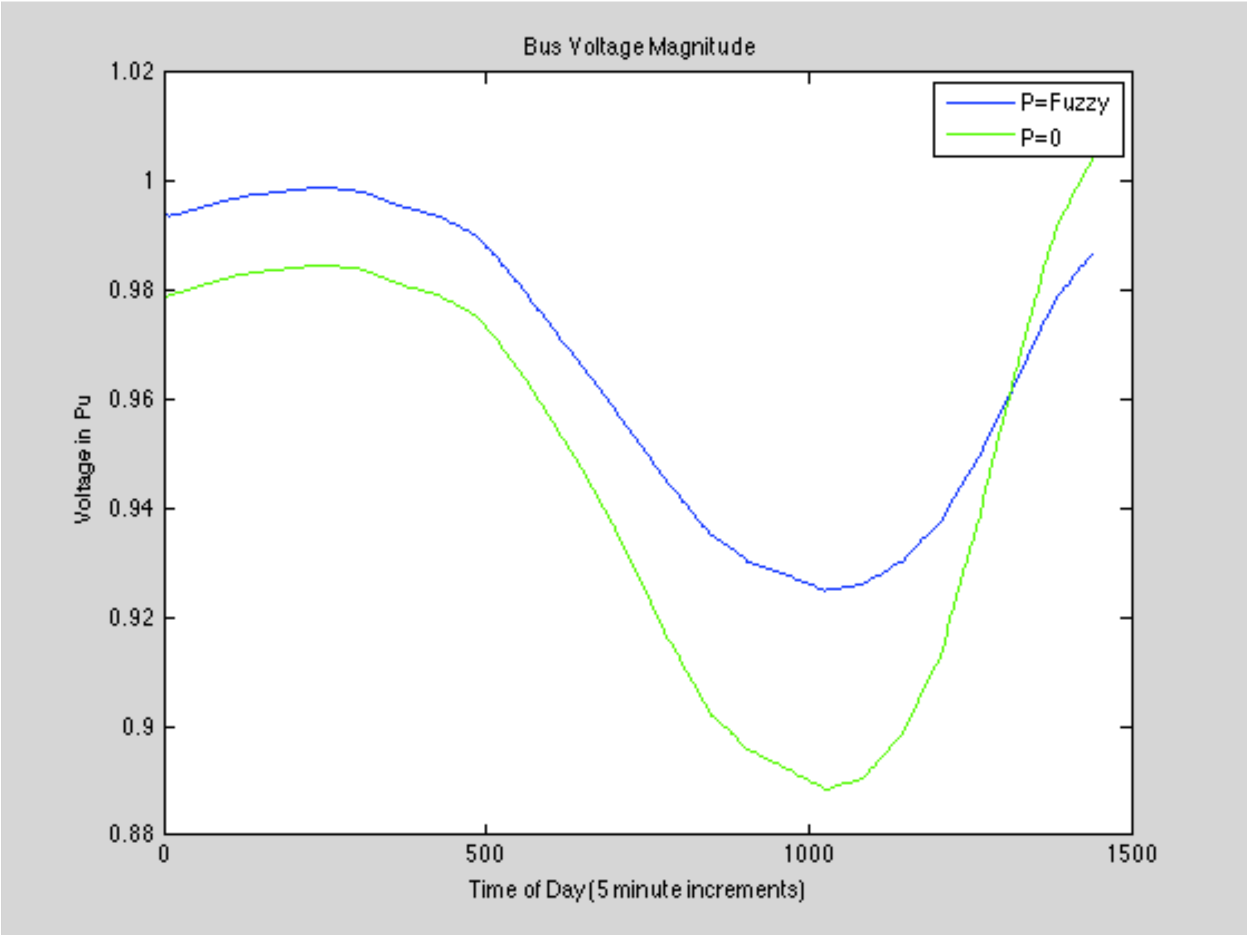

Figure 4.17 Voltage Dependent Fuzzy Controller (Voltage) at Bus 9, 6-gen

Fig. 4.18 shows the SOC of the charger for the Voltage Dependent Controller case in the 6-generator system. The SOC is significantly reduced compared to no charger. We can see why it is always discharging in Table 4.6, since this fuzzy controller is designed to be voltage dependent, and thus improve the voltage of the grid.

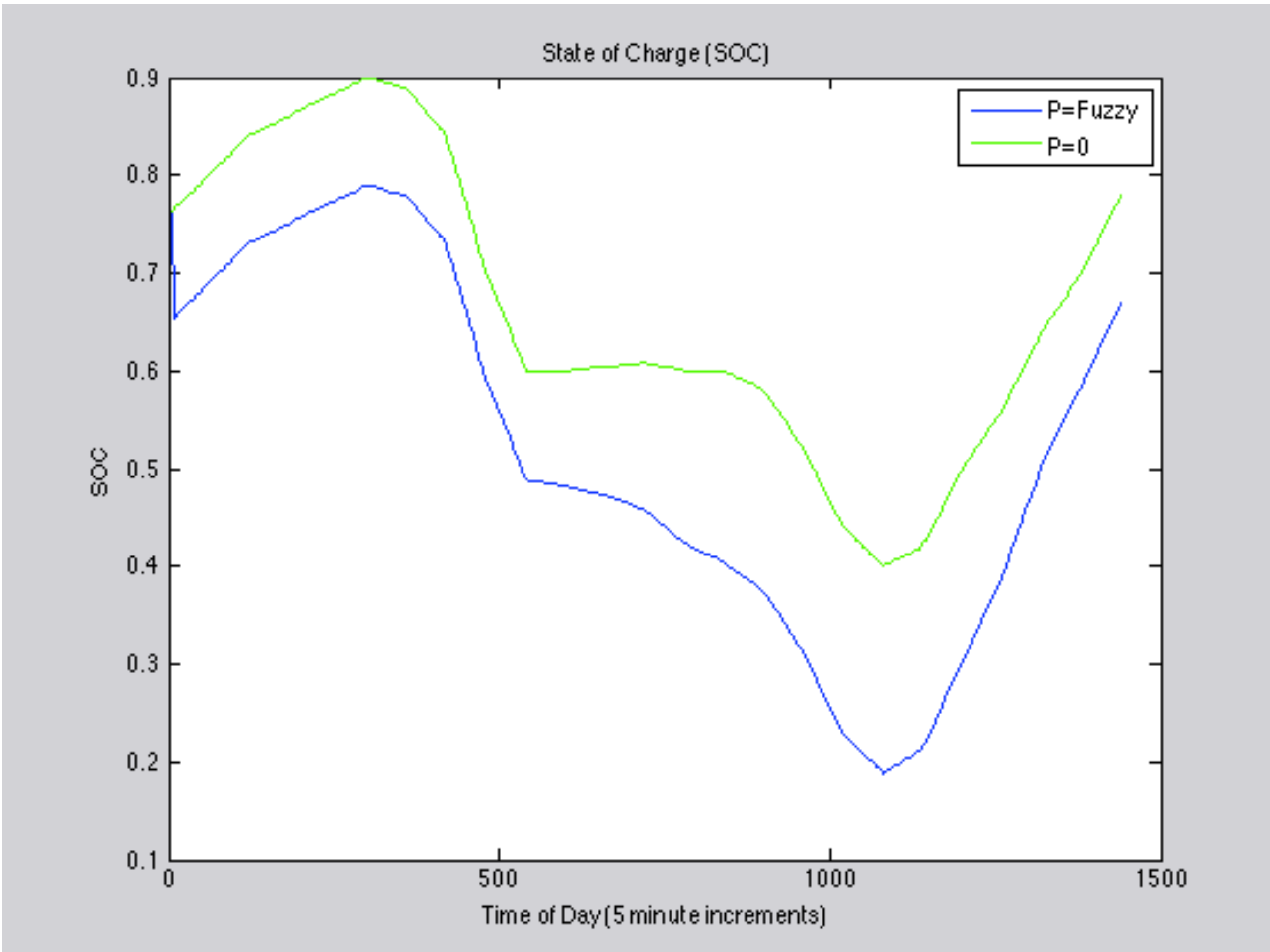

Figure 4.18 Voltage Dependent Fuzzy Controller (SOC) at Bus 9, 6-gen

4.3.7 Case 5 Balanced Controller

Lastly, a Balanced Fuzzy Controller is designed and tested. The Balanced Fuzzy Controller is like the Best Fuzzy Controller, but in this case the controller favors voltage stability a bit more than charging.

Looking at Table 4.7, we see that the zero charger output value crosses the table diagonally corner to corner. Looking at row 2, column 2 entry of Table 4.7, we see:

*"IF the SOC of the Electrical Vehicle is at **Very Low** level, and the grid Voltage is **Very Low**, THEN the charging rate should be Zero."*

V \ SOC	**VL**	**L**	**M**	**H**	**VH**
VL	Z	SN	MN	VN	VN
L	SP	Z	SN	MN	VN
M	MP	SP	Z	SN	MN
H	VP	MP	SP	Z	SN
VH	VP	VP	MP	SP	Z

Table 4.7 Balanced Fuzzy Controller

Figs. 4.19-4.22 further explain how this controller performs in regards voltage stability.

4.3.7.1 Balanced Controller, 16-Generator System, V2G at Bus 49

Fig. 4.19 shows the voltage magnitude at Bus 49 as a function of time of day for the Balanced Controller case. The 16-generator system, Bus 49 voltage is again affected very little.

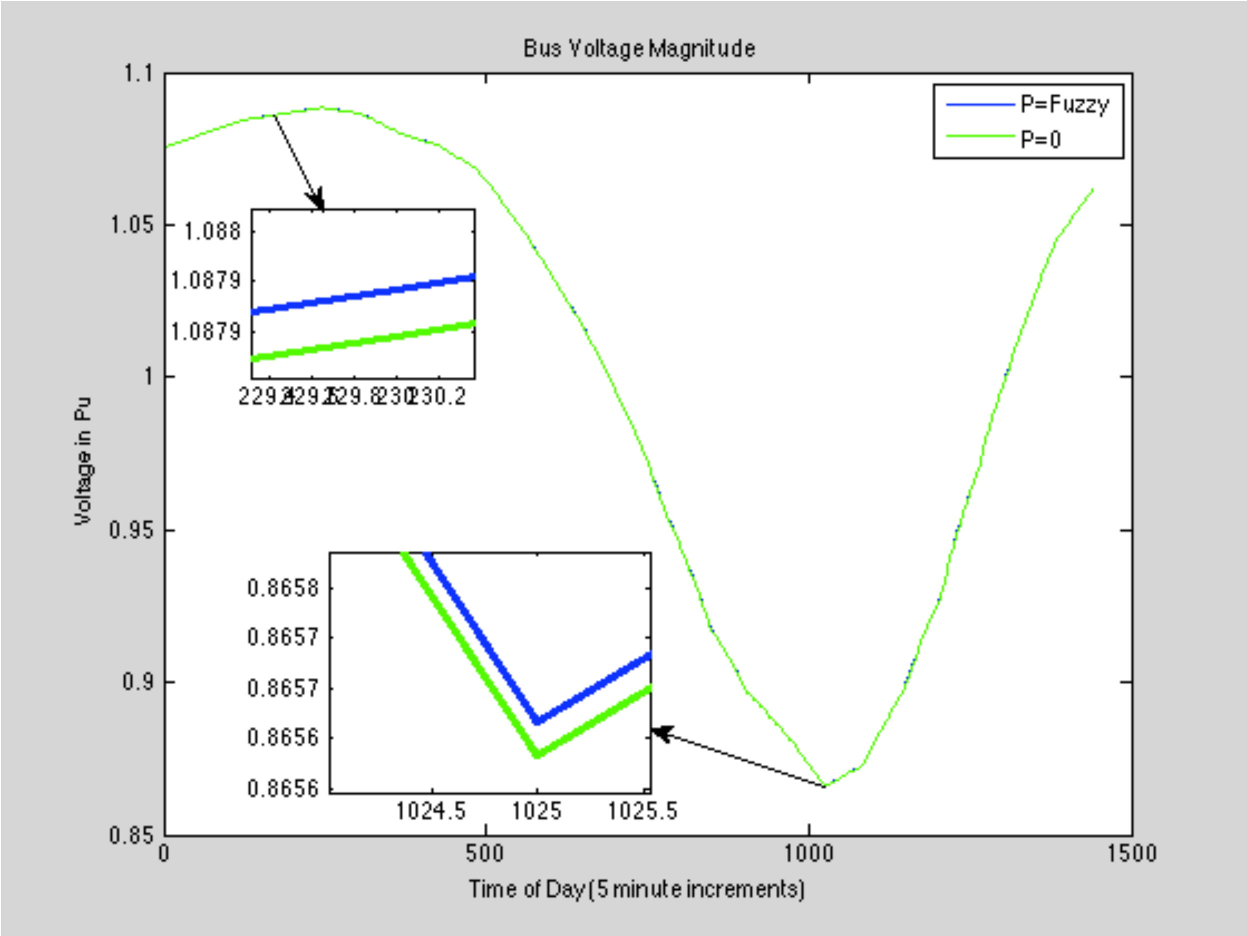

Figure 4.19 Balanced Fuzzy Controller (Voltage) at Bus 49, 16-gen

Fig. 4.20 shows the SOC of the V2G station for the Balanced Controller. We can see several periods when it's discharging. But we can see the difference of charging and discharging between the Best Controller case (Fig. 4.12) and the current case in that this charger is discharging much more of the time.

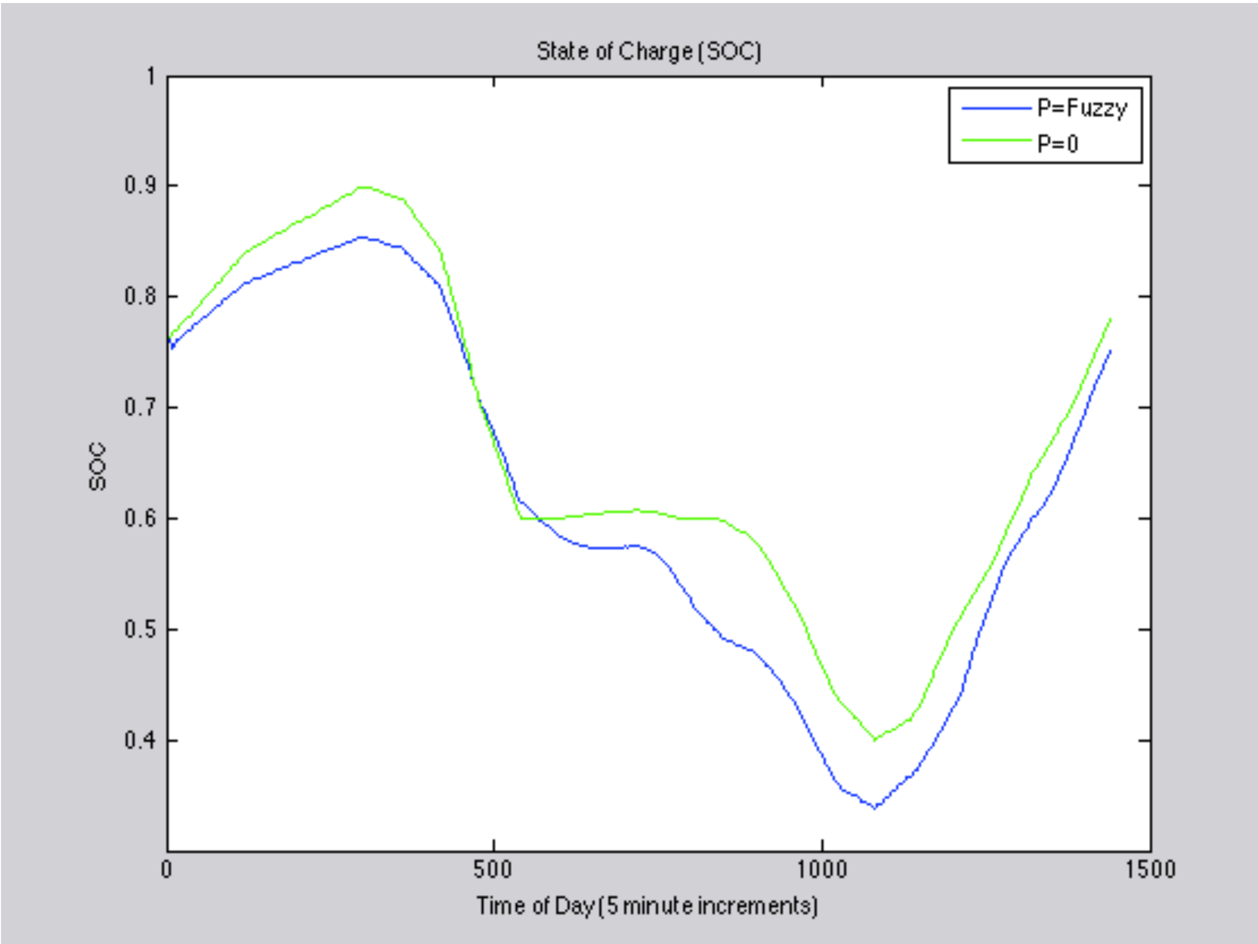

Figure 4.20 Balanced Fuzzy Controller (SOC) at Bus 49, 16-gen

4.3.7.2 Balanced Controller, 6-Generator System, V2G at Bus 9

Fig. 4.21 shows the voltage magnitude at Bus 9 for the Balanced Controller in the 6-generator system. The voltage profile is positively affected by the presence of the V2G. We observe that the V2G is reducing load on the system for several periods.

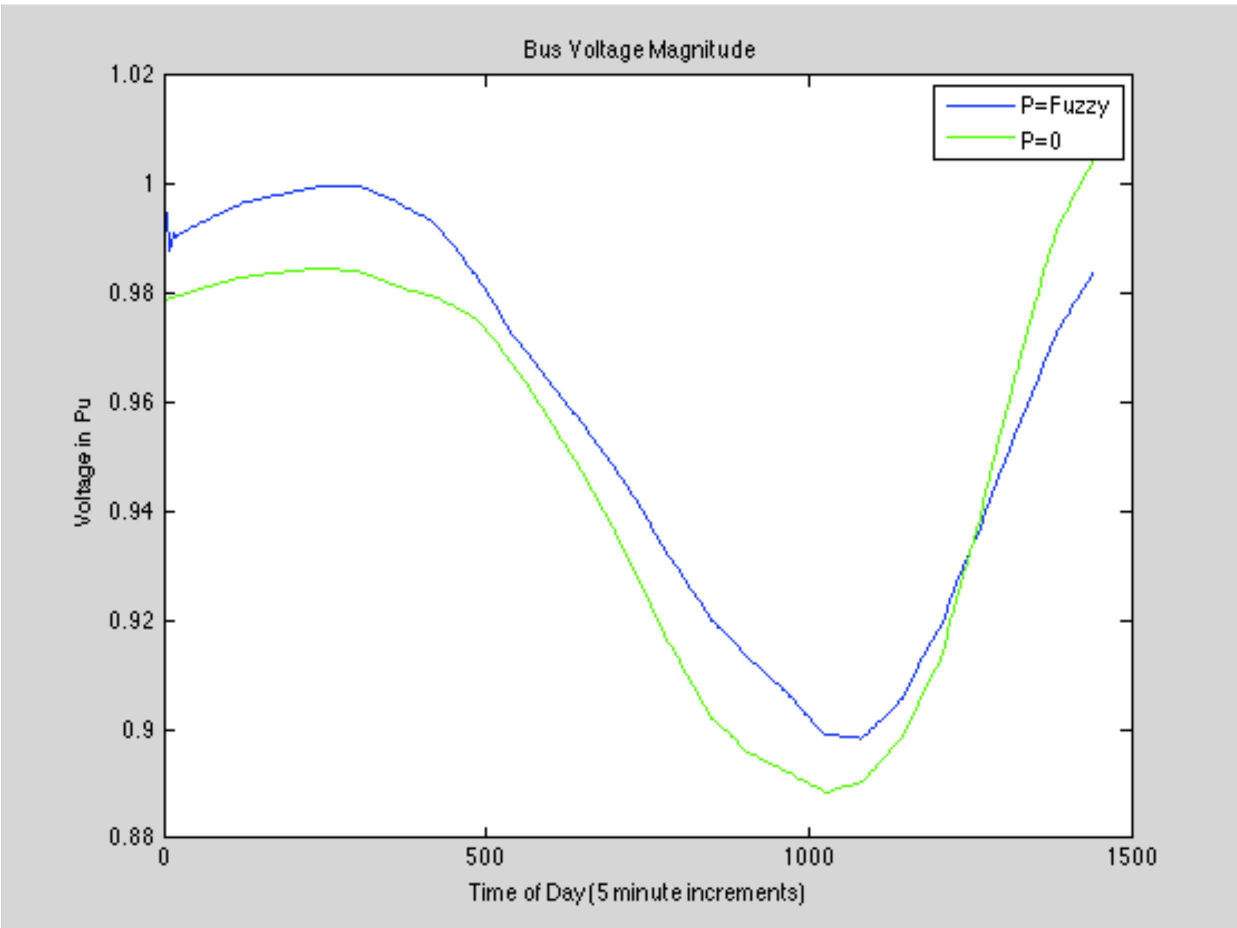

Figure 4.21 Balanced Fuzzy Controller (Voltage) at Bus 9, 6-gen

Fig. 4.22 shows the SOC of the station for the Balanced Charger in the 6-generator system. We can see that for all the periods it is discharging.

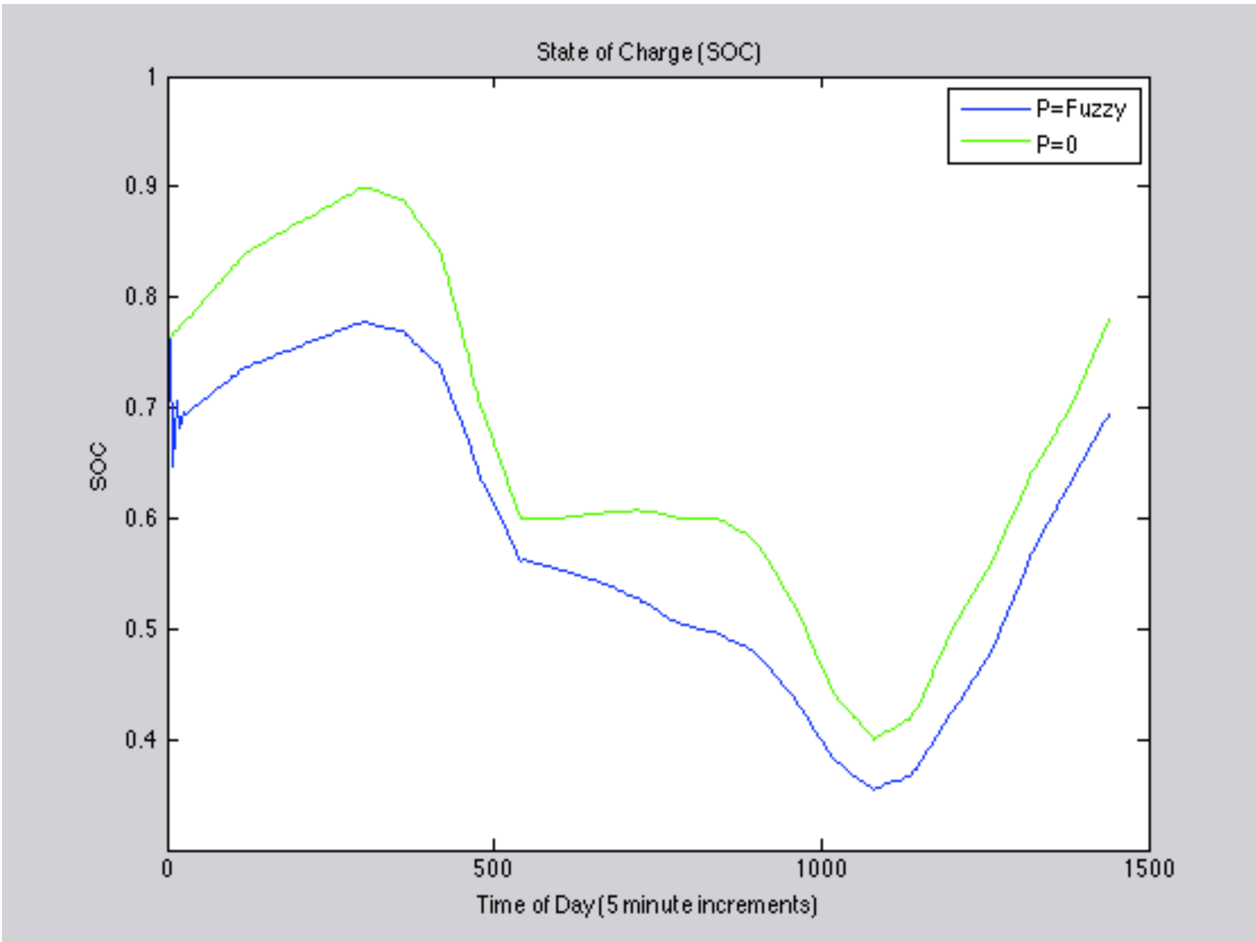

Figure 4.22 Balanced Fuzzy Controller (SOC) at Bus 9, 6-gen

4.3.8 Comparison of Results

In this section we compare the performances of the five cases designed for this thesis using graphs of the bus voltage, SOC, charger bus power, and V2G charger output.

4.3.8.1 16-Generator System, V2G at Bus 49

Fig. 4.23 shows the voltage magnitude at Bus 49 as a function of time of day for all the cases designed in this thesis. The voltage profile of all the cases is magnified to compare the performances of the fuzzy controllers. Case 1, the standard on/off Controller with no discharging has the lowest voltage, while the voltage dependent controller of Case 4 has the best voltage. We conclude that Case 2 is indeed the best fuzzy to meet most of the system's and the EV's needs, although the voltage differences are very small in all cases.

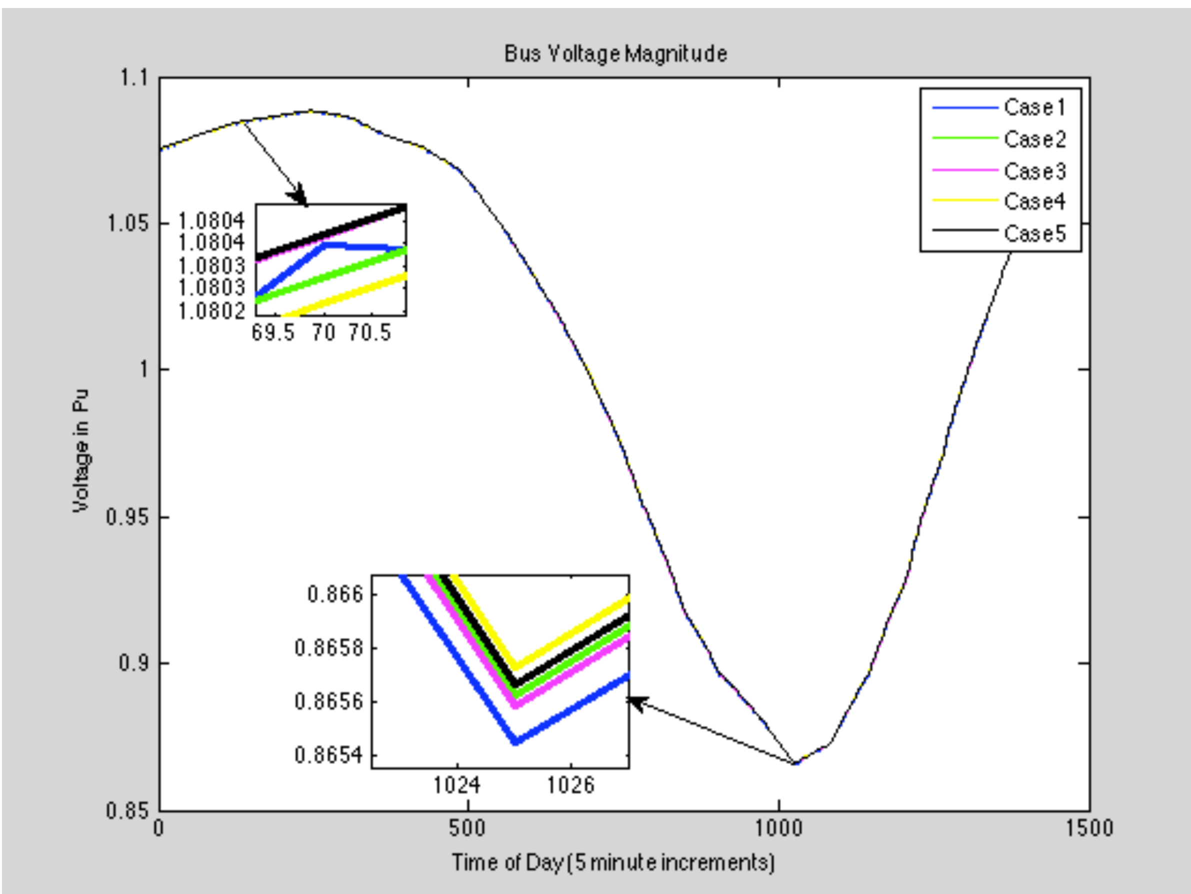

Figure 4.23 All Five Controllers (Voltage), at Bus 49, 16-gen

Fig. 4.24 shows the SOC of the V2G station for all the designed fuzzy logic controllers in this thesis. The SOC curve for the Standard Controller has a saw tooth pattern as explained previously. Note that Case 2 is in the middle of the five indicating that the Best Fuzzy Controller is the smartest controller designed to meet or best fill the needs of the grid and the EVs.

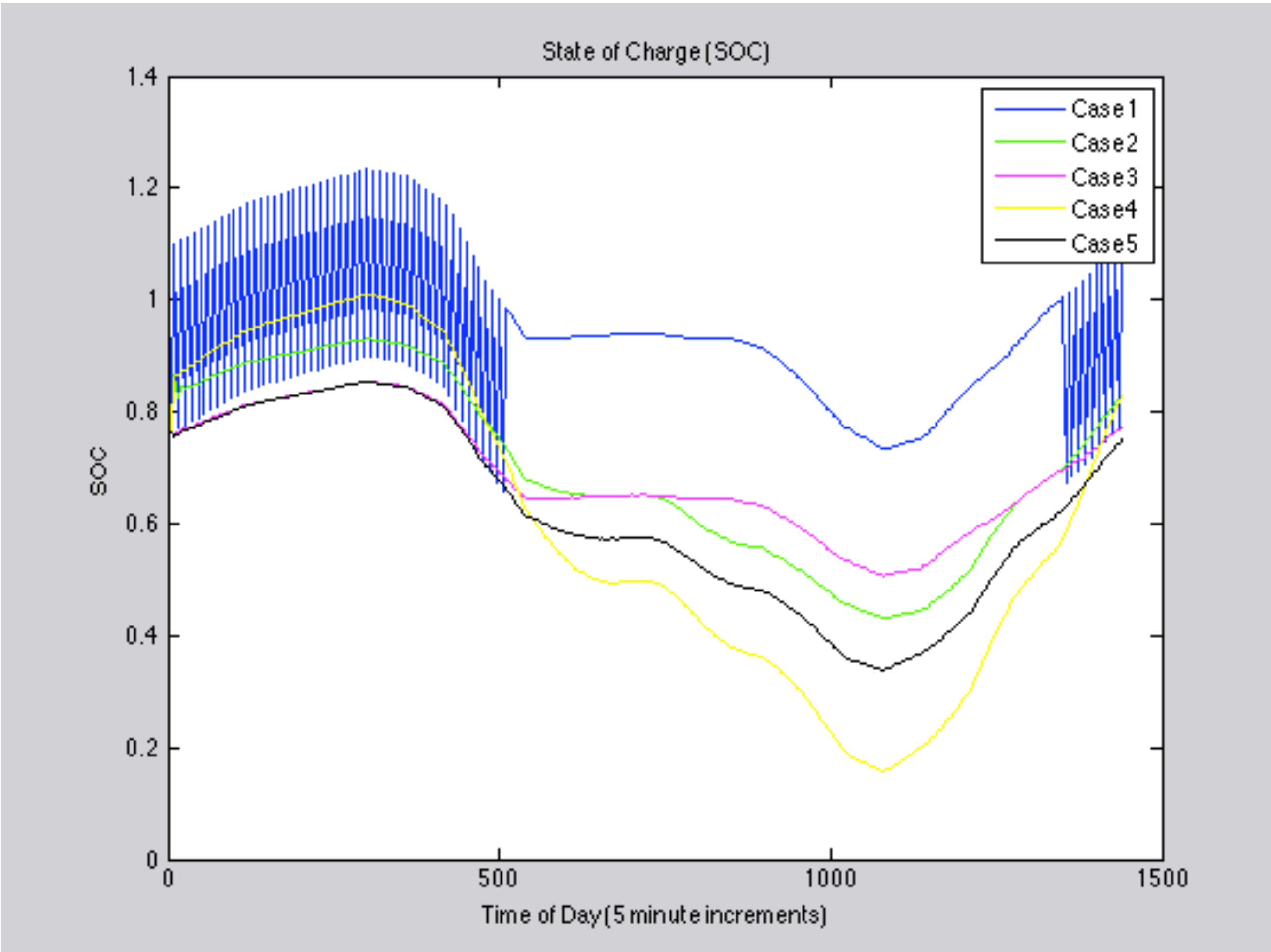

Figure 4.24 All Five Controllers (SOC) at Bus 49, 16-gen

Fig. 4.25 shows the load power at Bus 49 for all the designed fuzzy logic controllers in this thesis. Case 1, the Standard Controller, causes the higher load, while Case 4, the Voltage Dependent Controller, causes the least load.

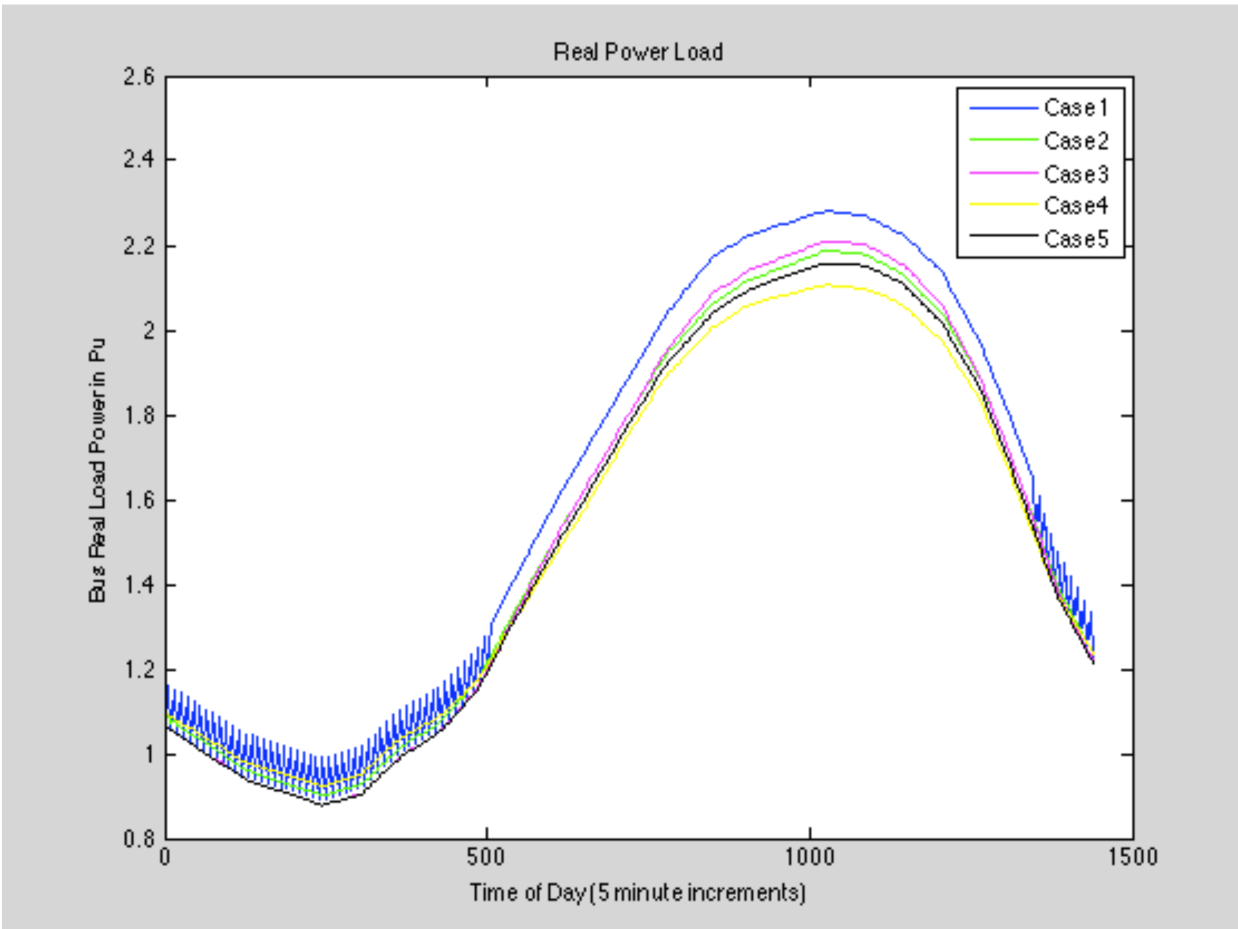

Figure 4.25 All Five Controllers (Load P) at Bus 49, 16-gen

Fig. 4.26 shows the controllers' output for all the designed fuzzy logic controllers in this thesis. The green curve for the Best Fuzzy case is again in the middle. We also note the similarity of Case 2 (Best Controller) and Case 5 (the Balanced Controller).

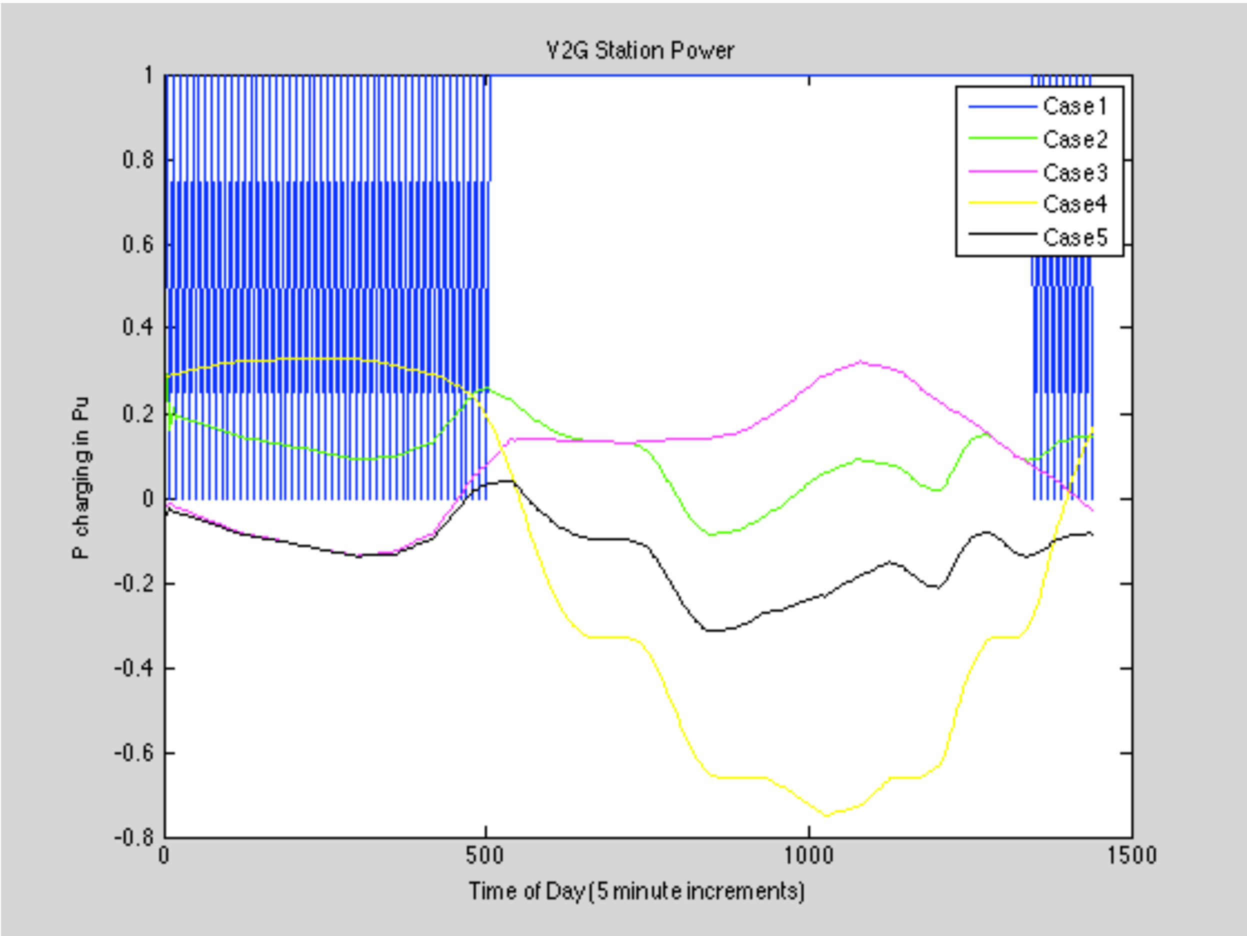

Figure 4.26 All Five Controllers (V2G Station Power) at Bus 49, 16-gen

4.3.8.2 6-Generator System, V2G at Bus 9

Fig. 4.27 shows the voltage magnitude at Bus 9 as a function of time of day for all the cases designed in this thesis. Again Case 1 gives the worst voltage profile, Case 4 gives the best, and Cases 2 and 5 give middle of the load results.

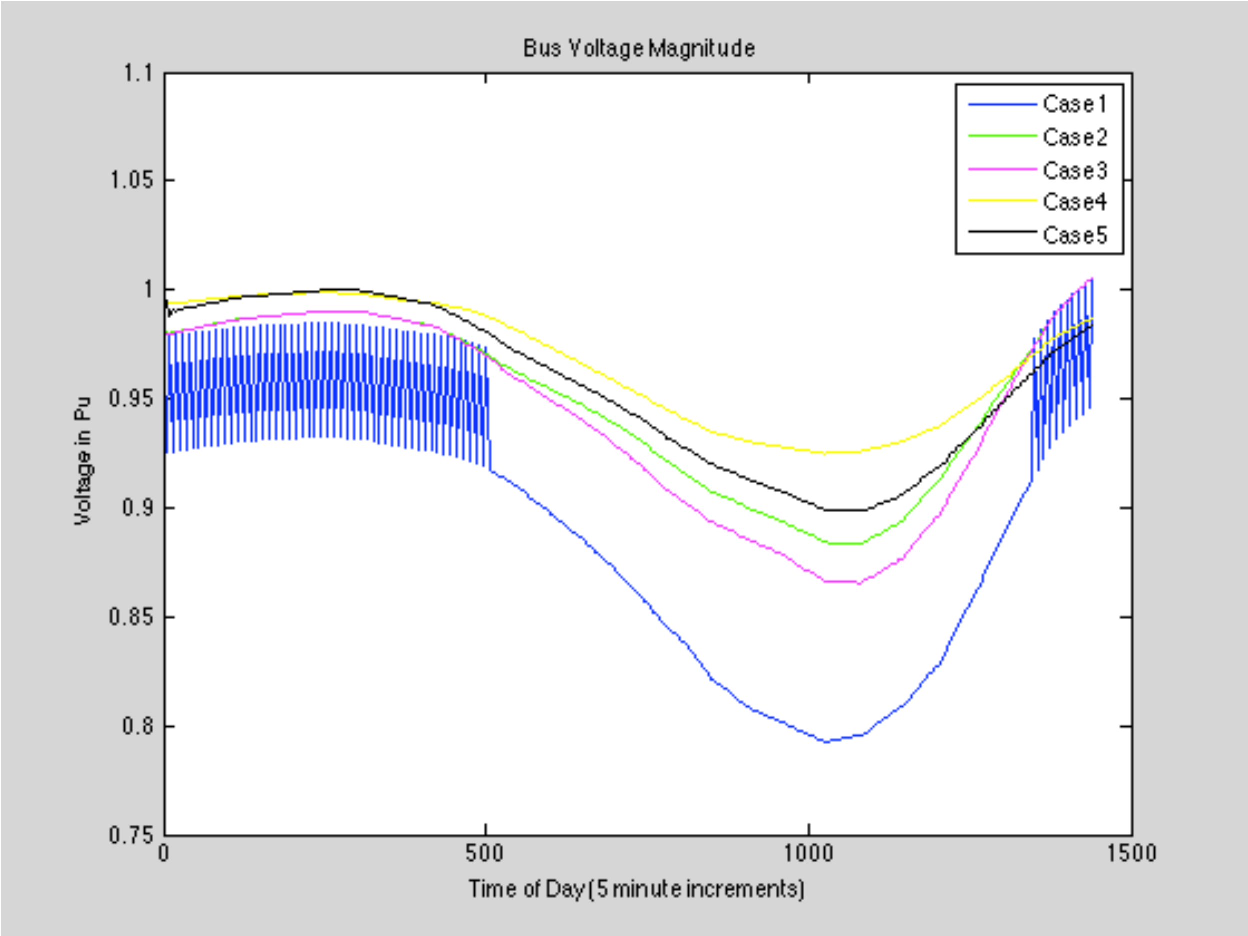

Figure 4.27 All Five Controllers (Voltage) at Bus 9, 6-gen

Fig. 4.28 shows the SOC of the V2G station for all the designed fuzzy logic controllers in this thesis. Note that Case 2 is in the middle of the five.

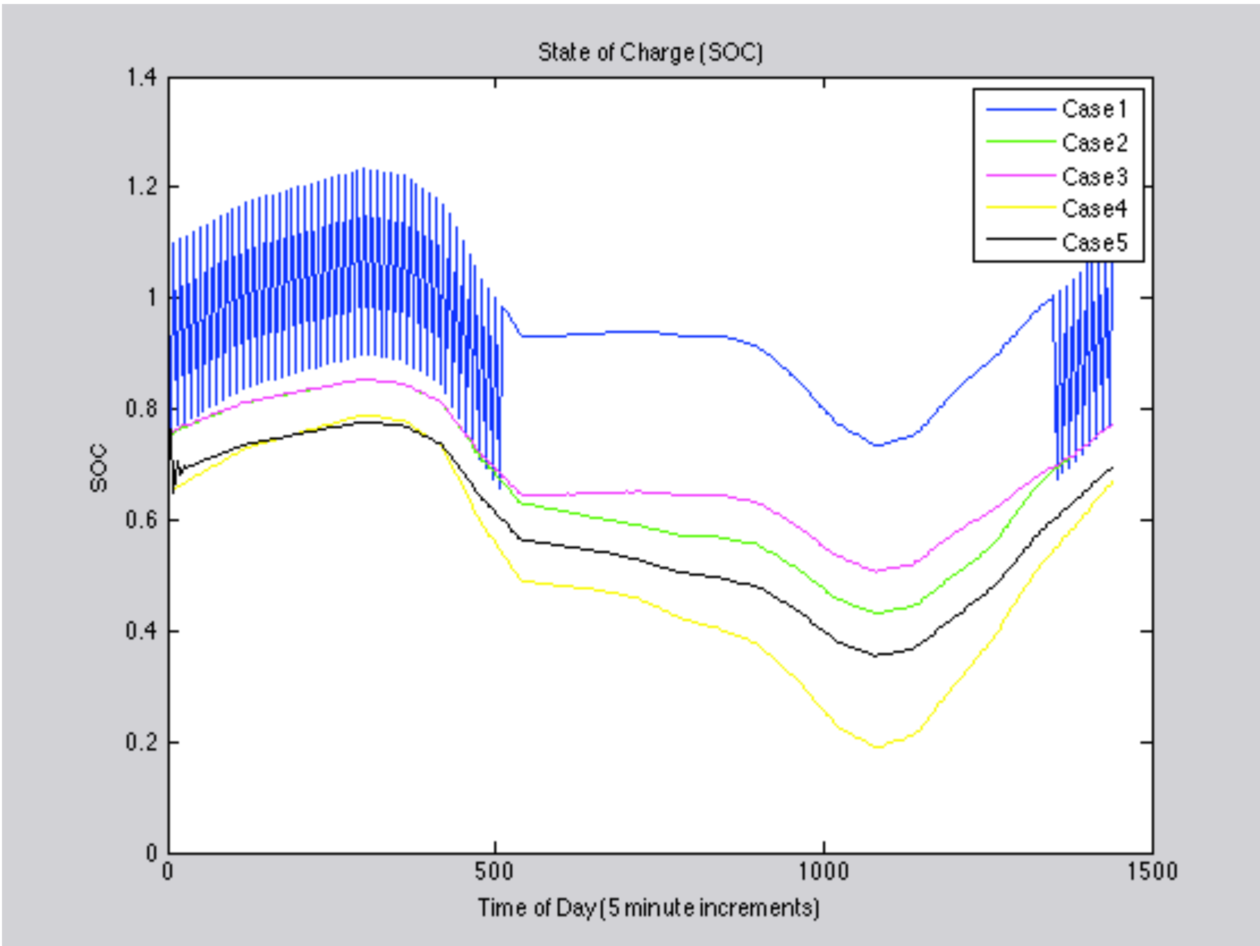

Figure 4.28 All Five Controllers (SOC) at Bus 9, 6-gen

Fig. 4.29 shows the Bus 9 load power for all the designed fuzzy logic controllers in this thesis. The results are similar to those seen in the 16-generator case.

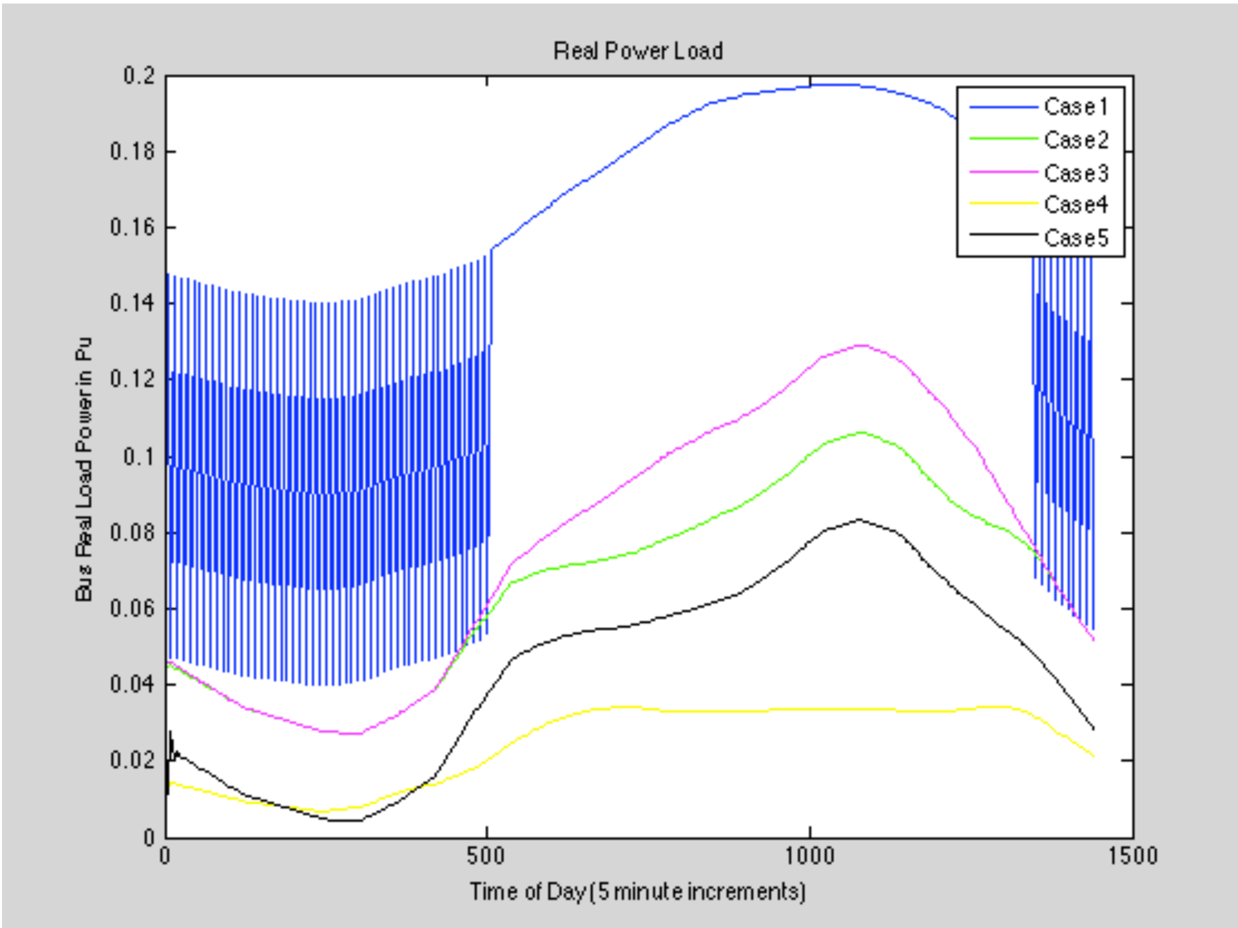

Figure 4.29 All Five Controllers (Load P) at Bus 9, 6-gen

Fig. 4.30 shows the chargers' output for all the designed fuzzy logic controllers in this thesis at Bus 9. Cases 2 and 5 are again the moderate cases.

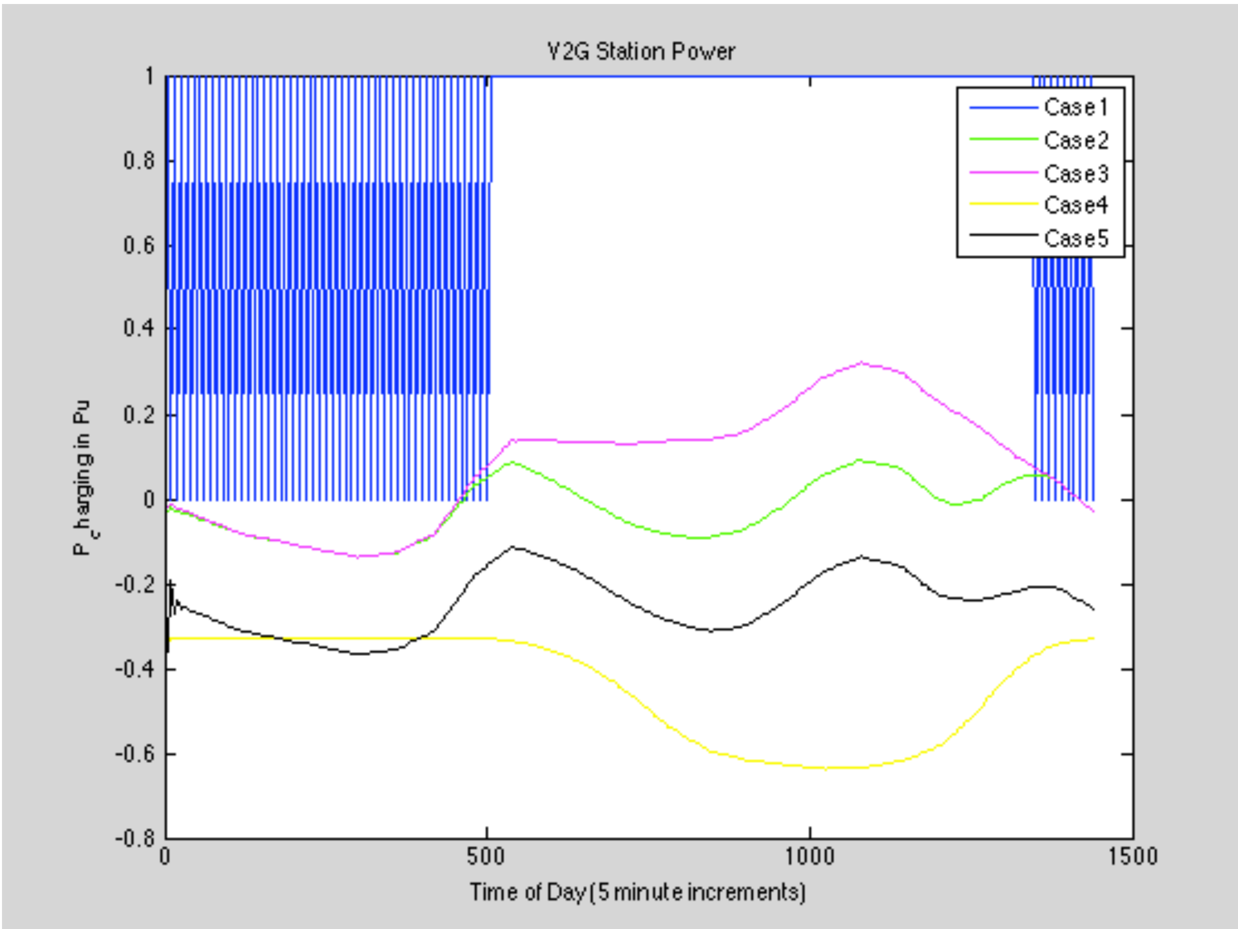

Figure 4.30 All five Fuzzy Controllers (V2G Station Power) at Bus 9, 6-gen

4.4 Weak Bus vs. Strong Bus

In this section V2G stations are placed individually at a weak voltage stability bus and a strong voltage stability bus in the 6-generator system to determine the effects of charger location. All of this analysis is done using the Case 2 Best Fuzzy Controller. A weak bus and a strong bus in the test system are chosen based on the eigenanalysis of the loadflow Jacobian. In particular, we studied the eigenvector associated with the maximum eigenvalue of the inverse of the Jacobian matrix. Strong busses had little connection to the critical eigenvalue as seen in the small size for the corresponding eigenvector elements. Weak busses were strongly tied to the critical eigenvalue based on the observation of larger elements in the associated eigenvector. The graphs generated for this analysis include:

- Bus voltages at the weak and strong busses for each case
- SOC for both situations
- Load P/Load Q at the bus
- V2G Station output in pu
- Maximum Eigenvalue of the inverse of the Jacobian as measure of system voltage stability

4.4.1 6-Generator System (Case 2), V2G at Bus 9 and Bus 1

Fig. 4.31 shows the bus voltage magnitude at Bus 9 (the weak bus) for the controller located at weak and strong buses. We see that when the V2G station is at the weaker bus, the highest voltage is slightly lower and lowest voltage is slightly higher.

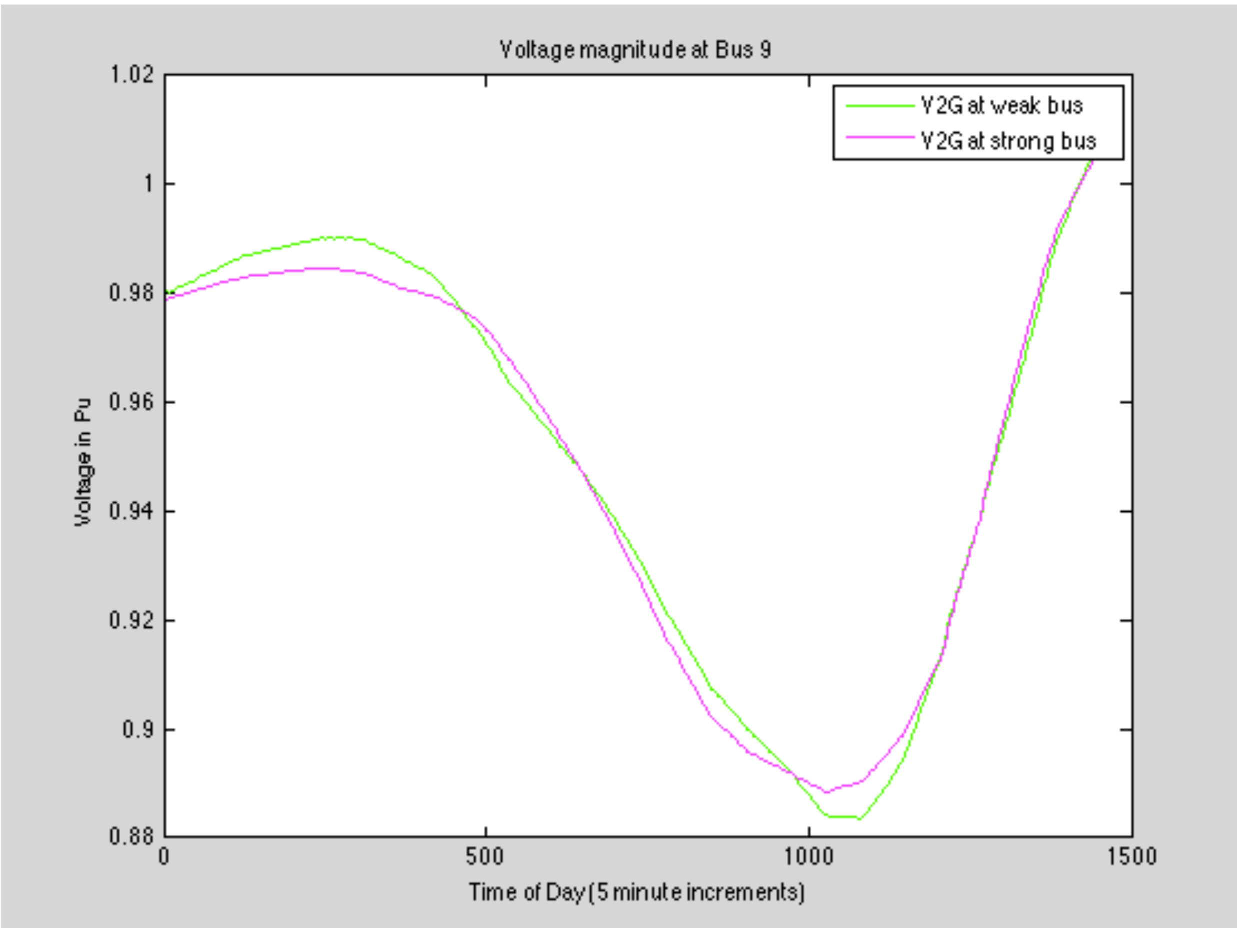

Figure 4.31 Best Fuzzy Controller (Voltage) weak vs. strong, V2G at Bus 9 , 6-gen

Fig. 4.32 shows the voltage magnitude at Bus 1 (the strong bus) for the controller placed at the weak and strong buses. In this case the controller at the weak bus yields slightly higher voltage at the low points, and lower voltages at the high points, although Bus 1's voltage stays much higher than the weak bus voltage.

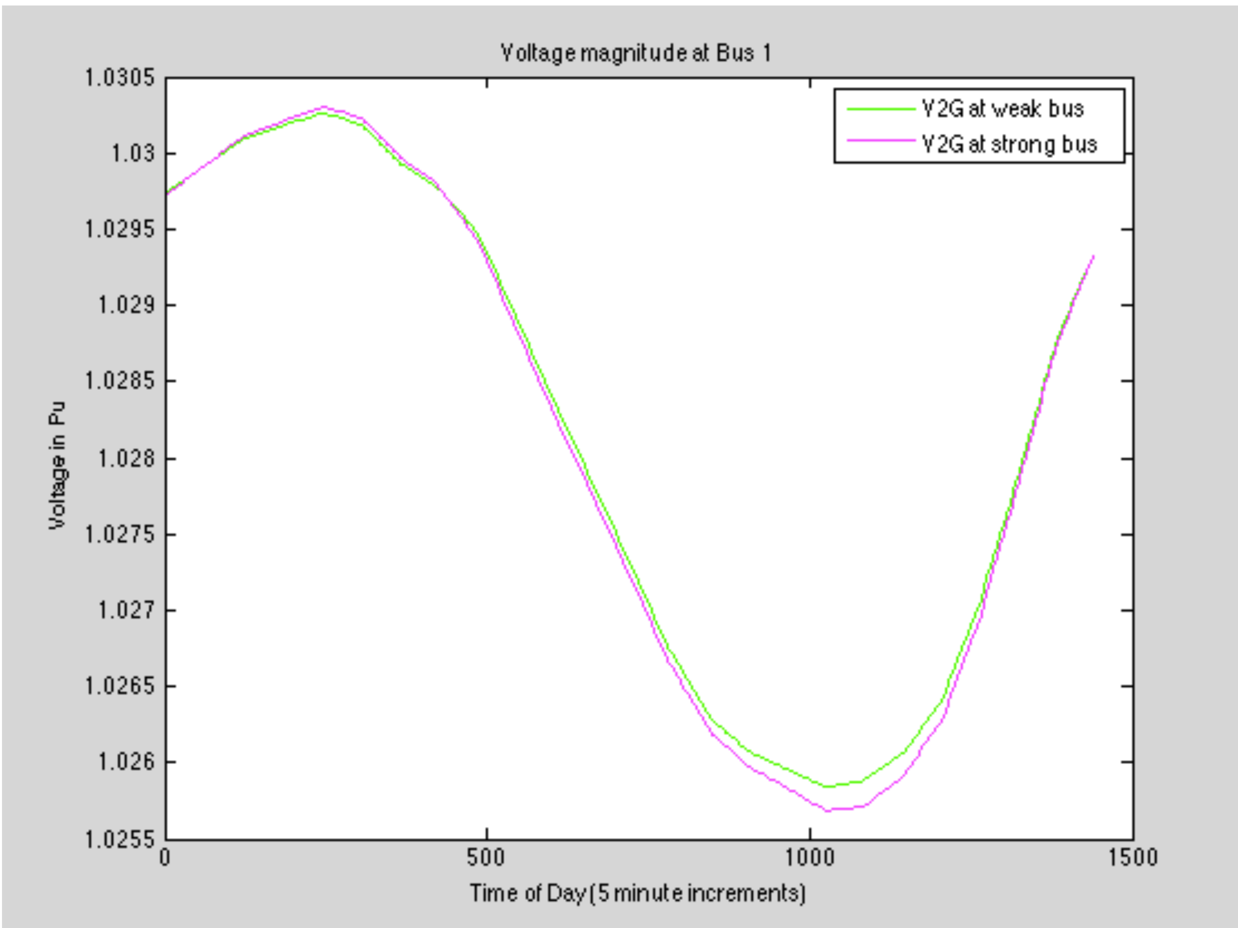

Figure 4.32 Best Fuzzy Controller (Voltage) weak vs. strong, V2G at Bus 9 & 1, 6-gen

Fig. 4.33 shows the SOC for the controller at the weak and strong buses to compare between the two. The V2G station at the weak bus is more variable, with a slightly lower maximum SOC and a lower minimum SOC. Thus placing the controller at the strong bus allows more charging.

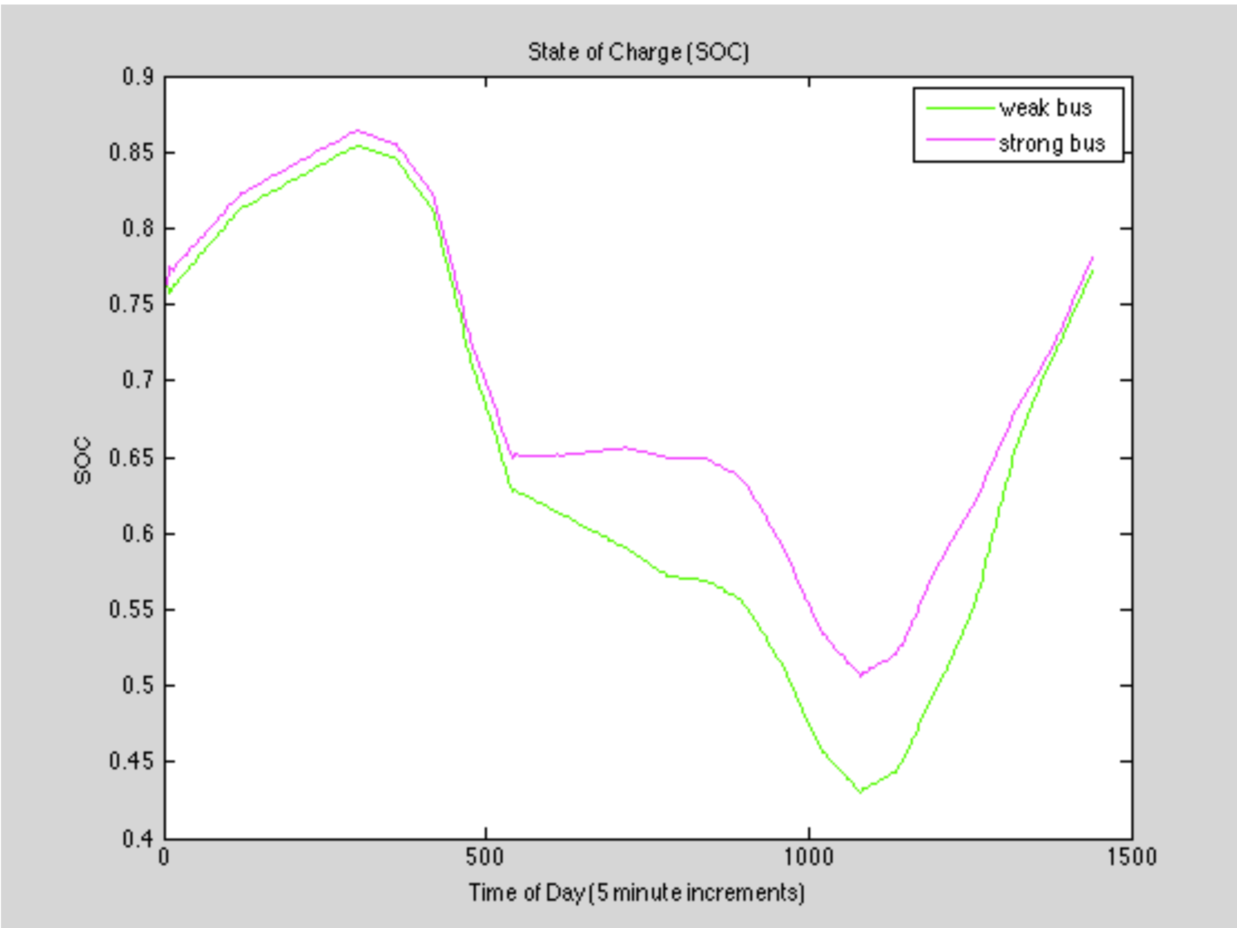

Figure 4.33 Best Fuzzy Controller (SOC), weak vs. strong, V2G at Bus 9 & 1, 6-gen

Fig. 4.34 shows the Bus 9 load power for the controller placed at the weak and strong buses. Bus 9 is the weak bus and we see that the charger makes its power range larger.

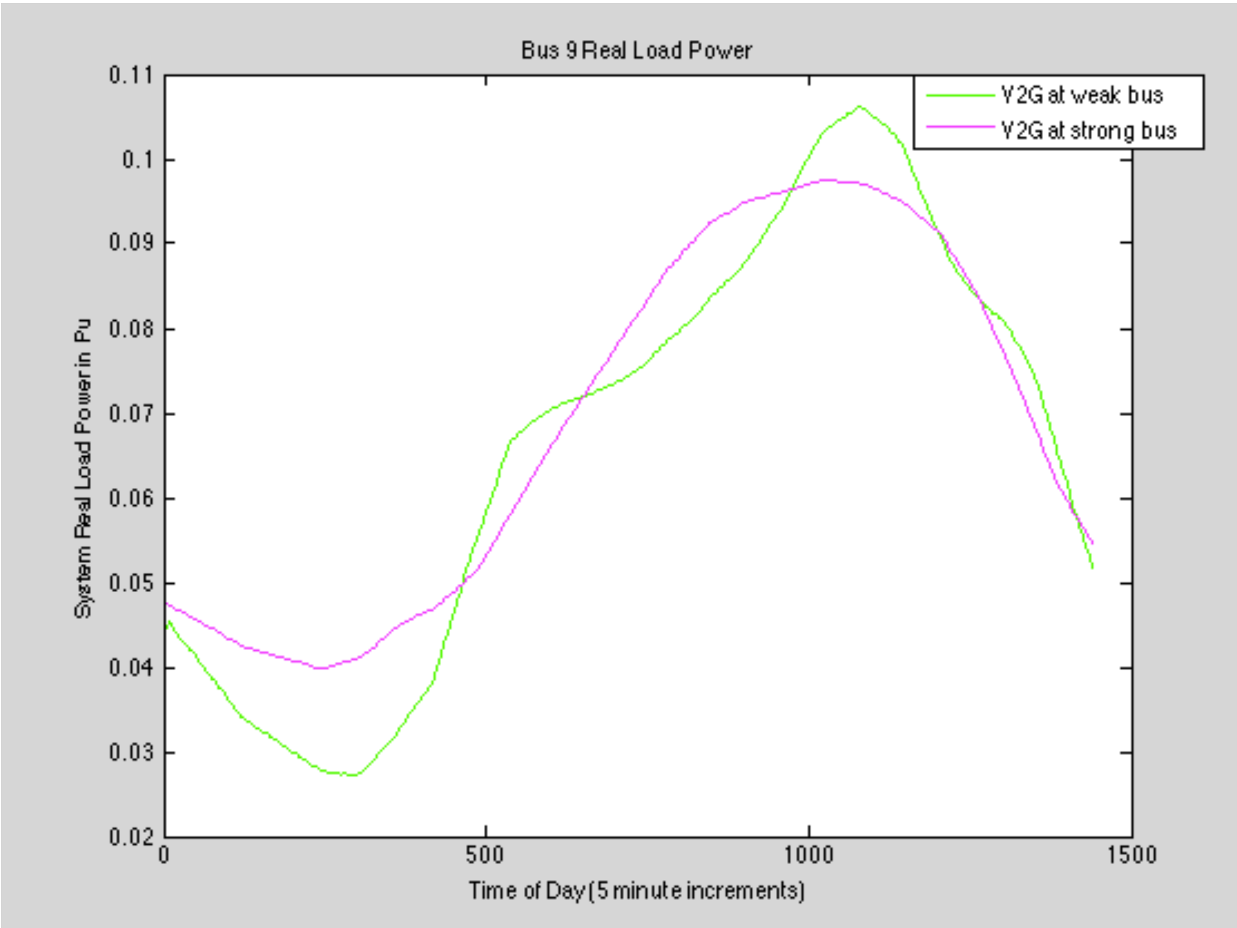

Figure 4.34 Best Fuzzy Controller (Load P) weak vs. strong, V2G at Bus 9, 6-gen

Fig. 4.35 shows the Bus 1 load power for the controller placed at the weak and strong buses. Again placing the charger at Bus 1 causes it to have a larger range of power values.

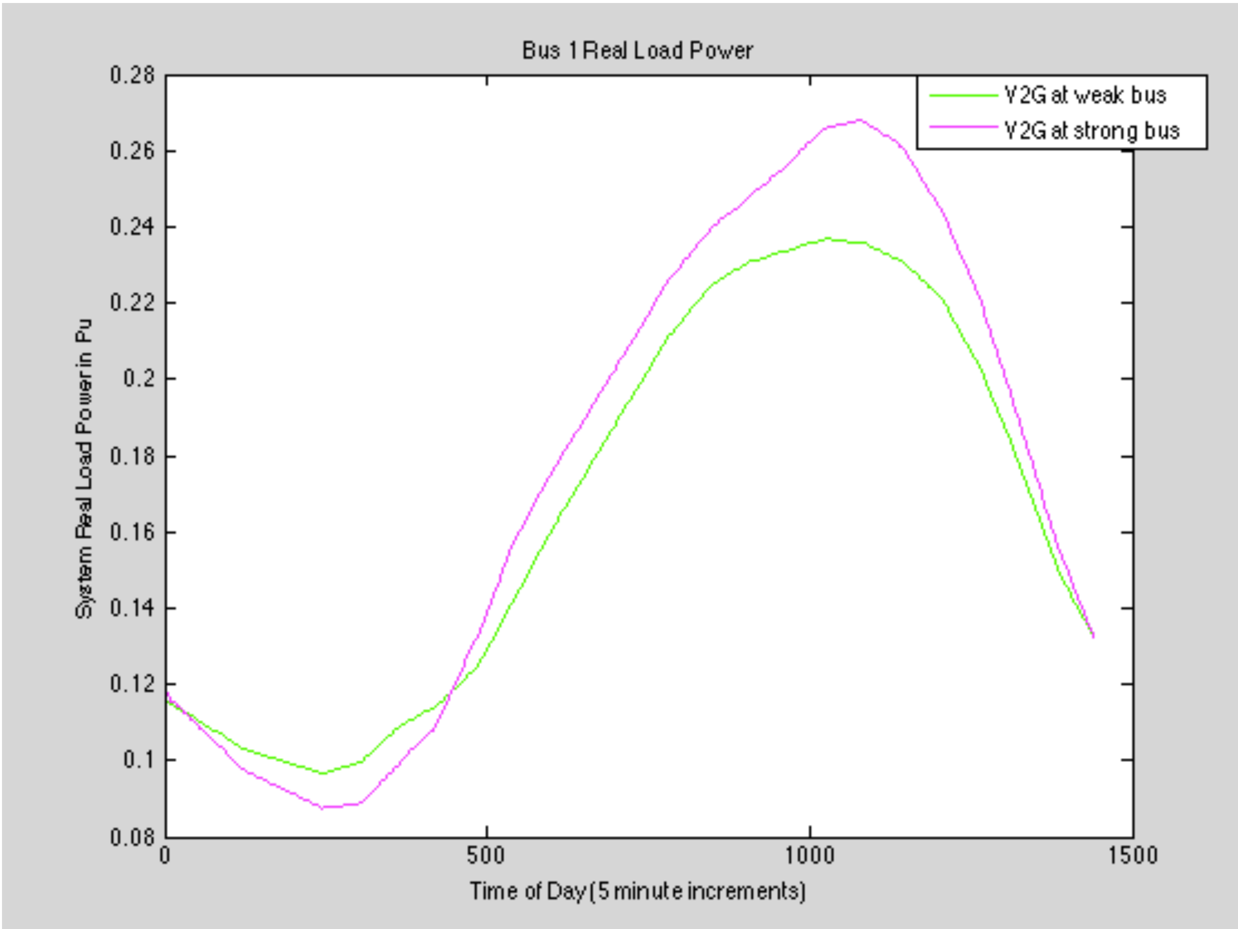

Figure 4.35 Best Fuzzy Controller (Load P) weak vs. strong, V2G at Bus 1, 6-gen

Fig. 4.36 shows the controllers' output for the weak and strong buses. This verifies the data seen in the SOC curves.

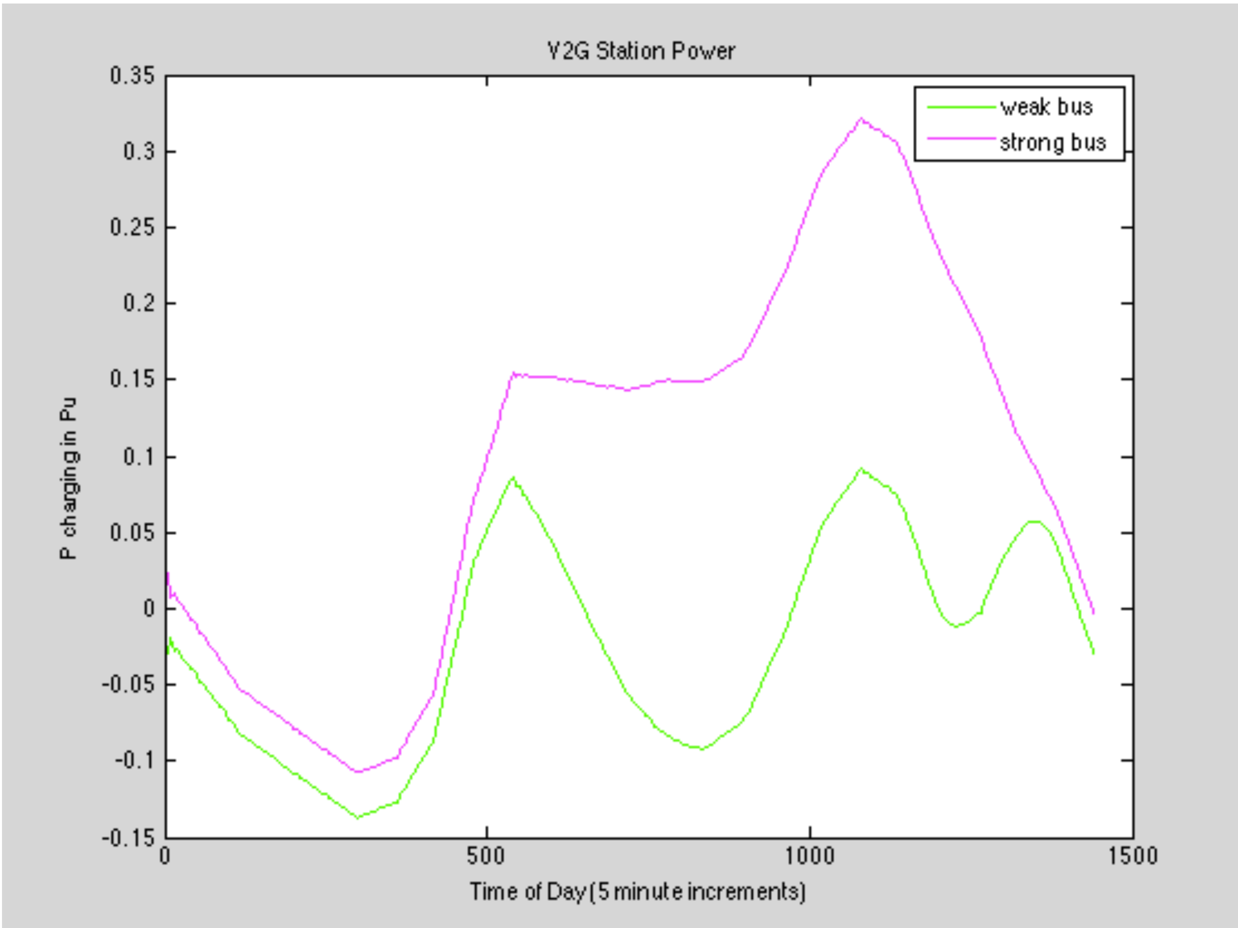

Figure 4.36 Best Fuzzy Controller (V2G Power) weak vs. strong, V2G at Bus 9&1, 6-gen

Fig. 4.37 shows the maximum eigenvalues for the weak and strong bus cases. The strong bus case has a slightly lower minimum eigenvalue. The maximum eigenvalue was 3.57 for the weak bus case, as apposed to 3.52 for the strong bus case.

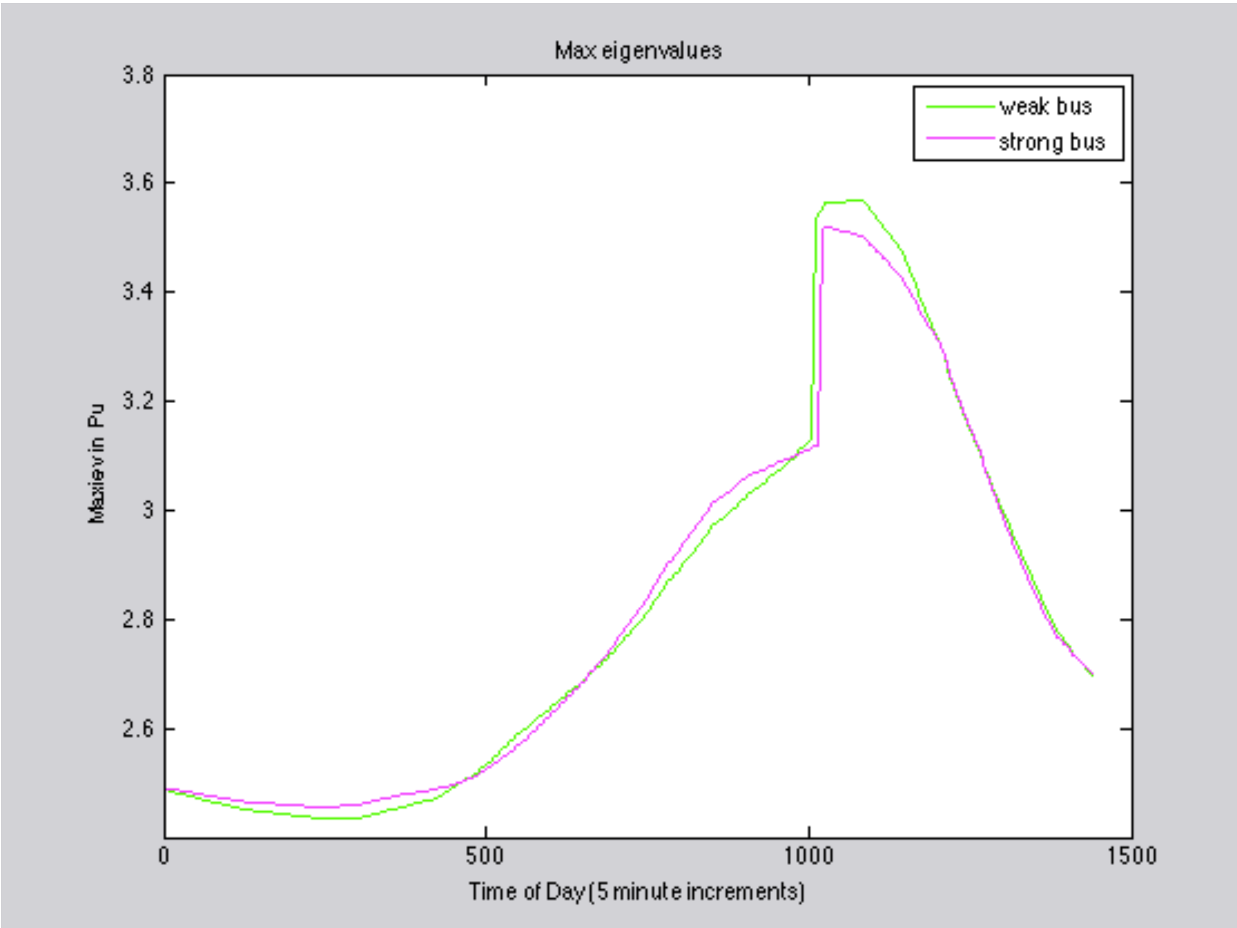

Figure 4.37 Best Fuzzy Controller (Max eigenvalue) weak vs. strong,V2G at Bus 9&1,6-gen

4.5 Q-Charging vs. P-charging

This section studies discharging using Q (Vars) to determine if it would be more beneficial more than discharging P (real) power to the grid. Since Q is strongly tied to voltage, it is anticipated that providing VARs would help the voltage stability more than providing real power. It is assumed that providing VARs instead of Watts would not be a complicated power electronics problem for the charging stations and the battery. A sequence of graphs (Figs. 4.38-4.43) are generated to fully examine the benefit of discharging in Q instead of P. All of this analysis is done using Case 4, the Voltage Dependent Controller for the 16- generator system of this thesis. The V2G is at Bus 49 of the 16-generator system. The graphs include:

- Voltage magnitude at Bus 49
- SOC
- Load P and Q at Bus 49
- P_charging/Q_charging
- Maximum Eigenvalue

4.5.1 16-Generator system (Case 4), V2G at Bus 49

Fig. 4.38 shows the voltage magnitude at Bus 49 of the P and Q based controllers for the Voltage Dependent Fuzzy. As we can see, the Q-based controller improves the voltage profile a bit more than the P-based controller. This is the most significant change in voltage seen at Bus 49 of the 16-generator system.

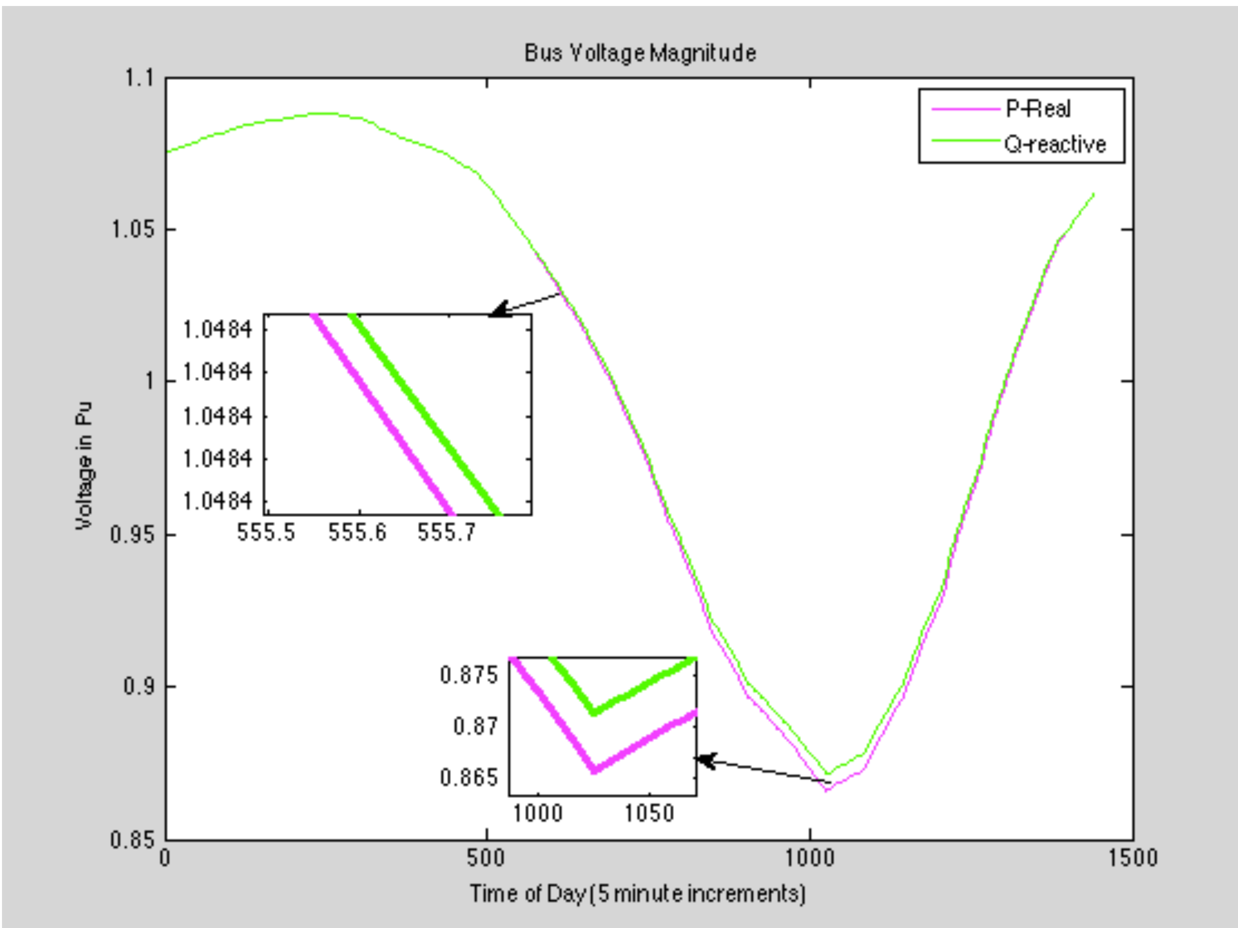

Figure 4.38 Voltage Dependent Fuzzy Controller (Voltage) at Bus 49, 16 gen

Fig. 4.39 shows the SOC of the V2G station comparing the discharging of both P and Q based controllers. Discharging using Q is bit more helpful than discharging with P, in that the SOC remains a bit higher.

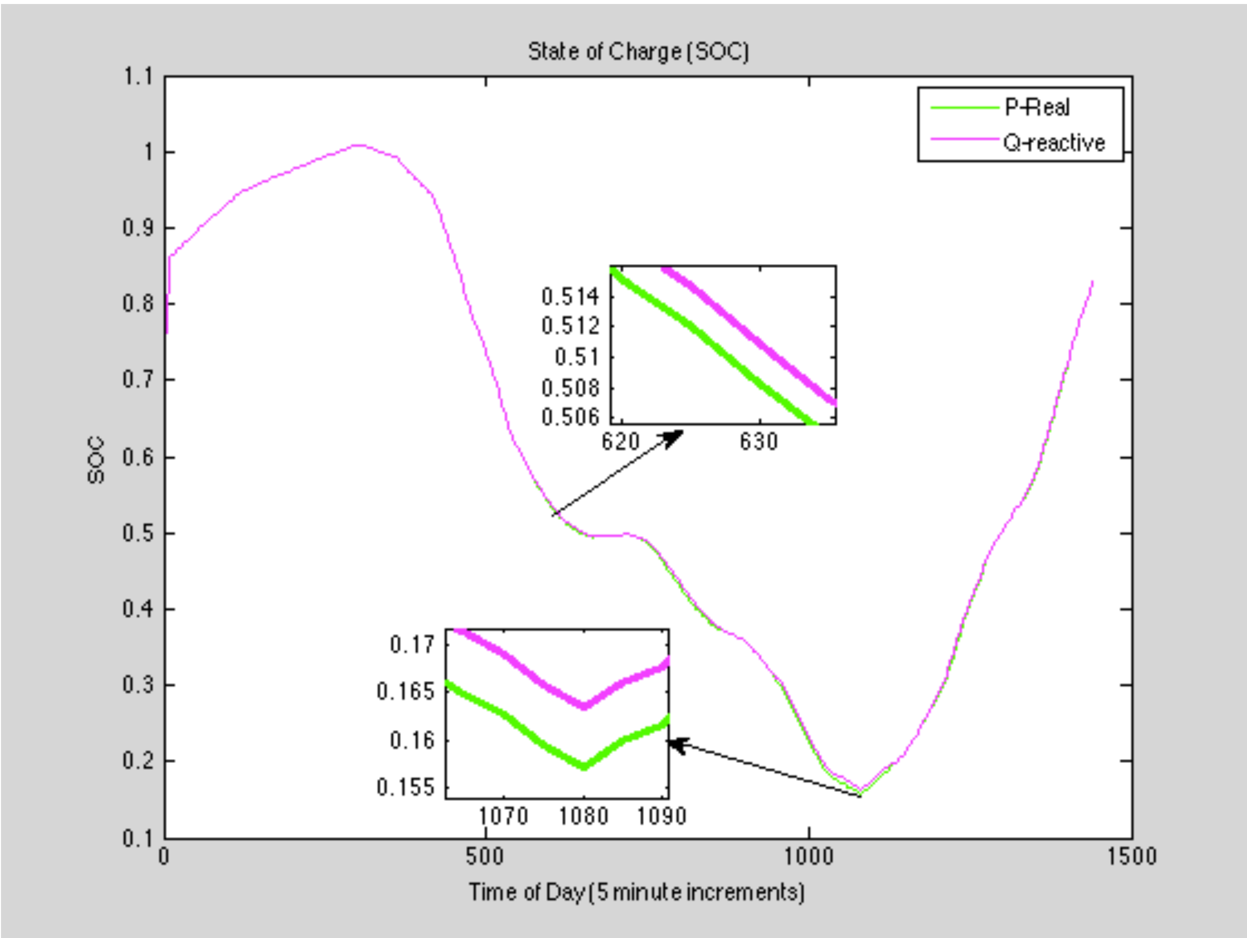

Figure 4.39 Voltage Dependent Controller (SOC) at Bus 49, 16-gen

Fig. 4.40 shows the load power at Bus 49 as a function of time of day. The P load is slightly lower at the maximum point, though the scale makes the difference hard to see.

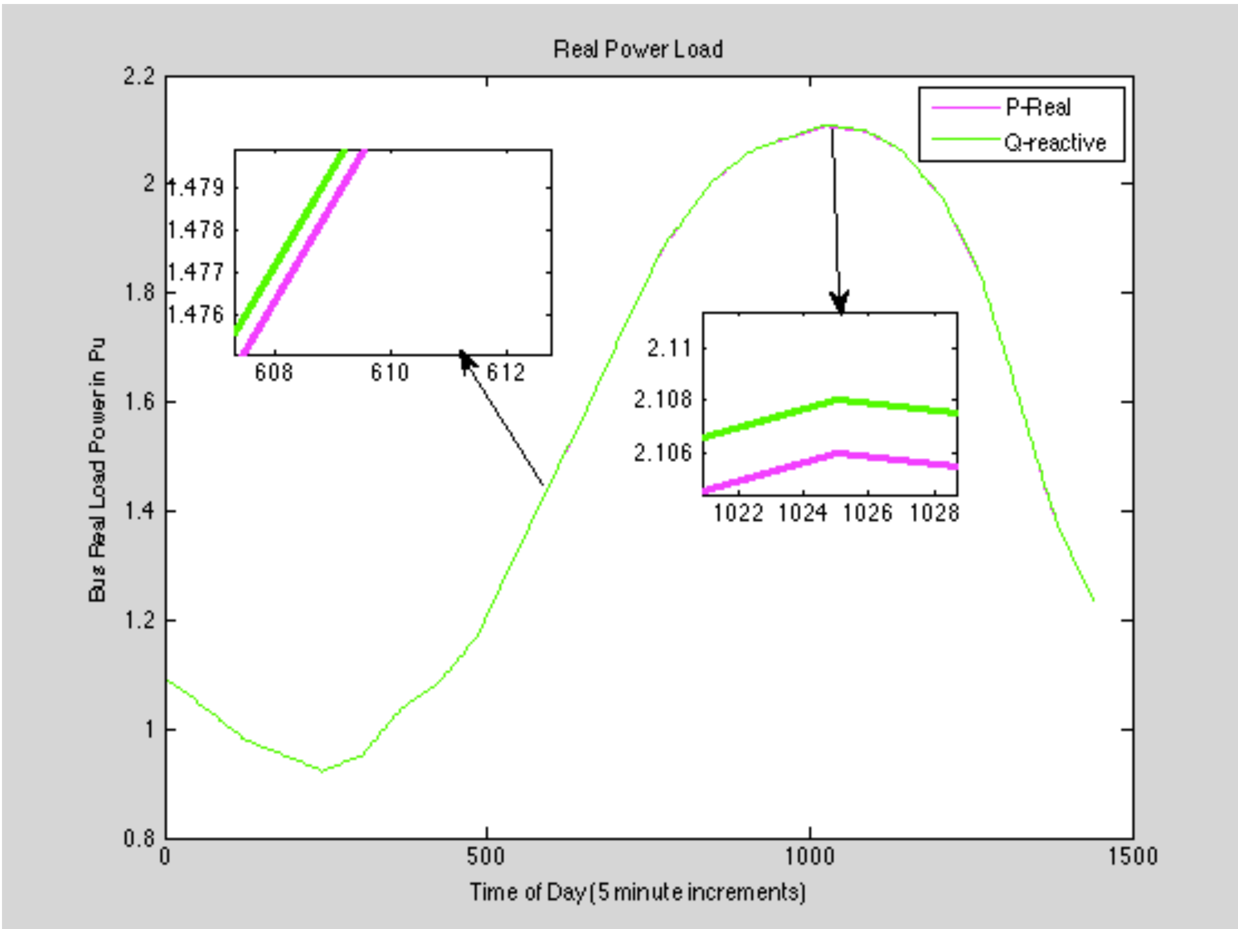

Figure 4.40 Voltage Dependent Fuzzy Controller (Load P) at Bus 49, 16-gen

Fig. 4.41 shows the Reactive power load at Bus 49 as a function of time of day. The Q load profile is significantly lower for the Q-based controller. This is evidence of the controller's design.

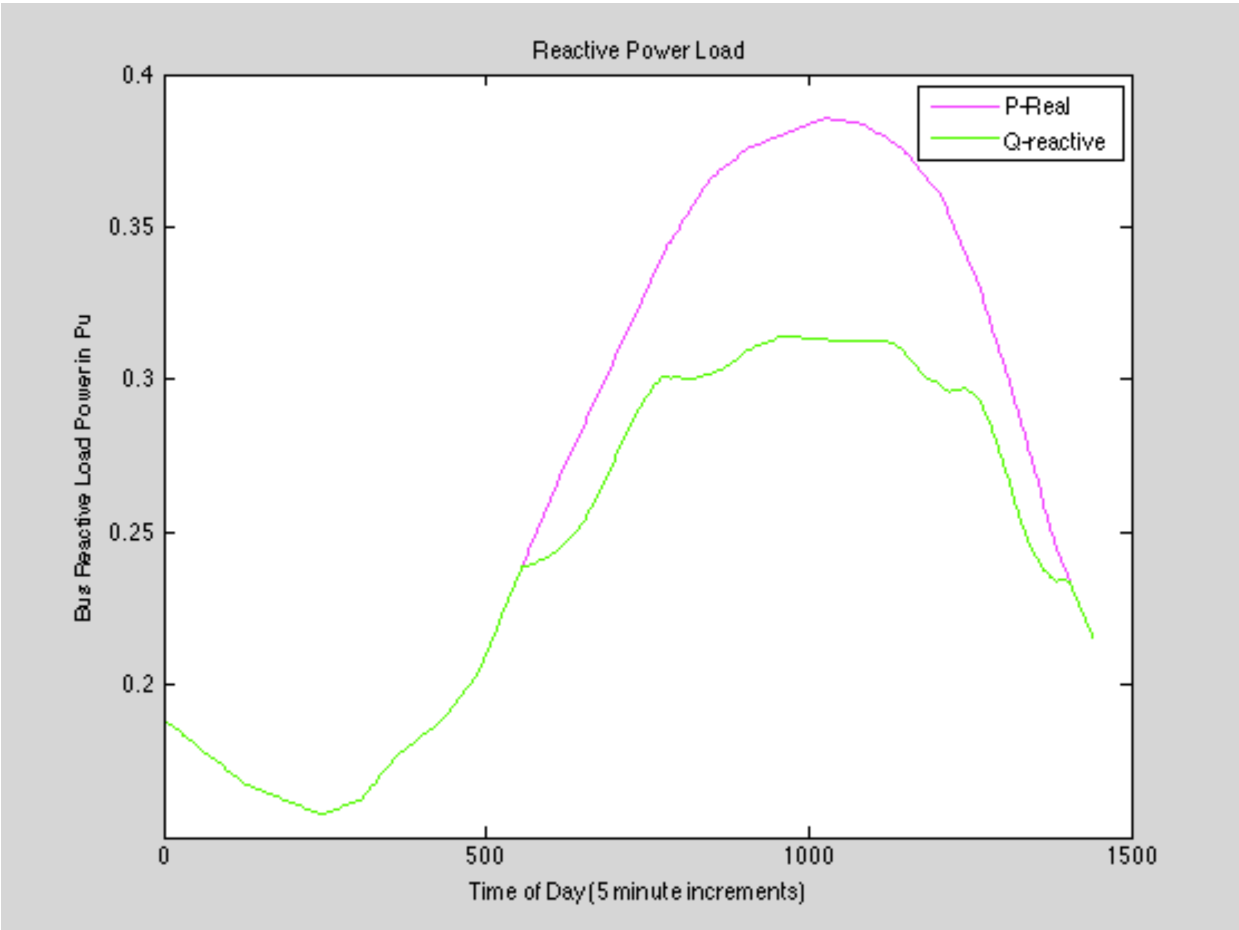

Figure 4.41 Voltage Dependent Controller (Load Q) at Bus 49, 16-gen

Fig. 4.42 shows the controllers' output at Bus 49 as a function of time of day. We can see that Q-based controller takes a bit less power to get better results than the P-based controller.

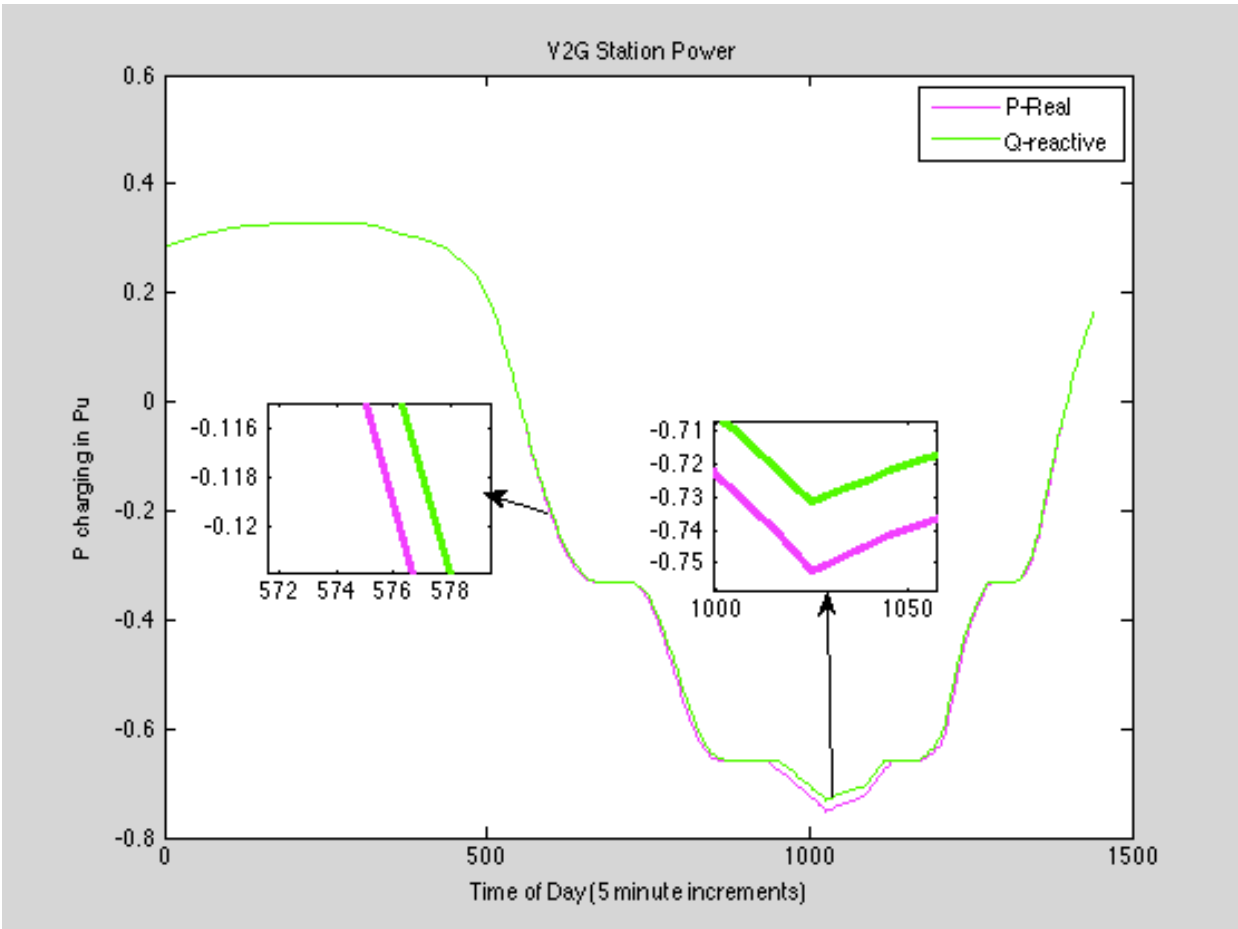

Figure 4.42 Voltage Dependent Controller (V2G Station Power) at Bus 49, 16-gen

Fig. 4.43 shows the maximum eigenvalues of the inverse loadflow Jacobian as a function of time of day. The eigenvalue profile confirms that discharging with Q is a bit more helpful in regards to the system voltage stability.

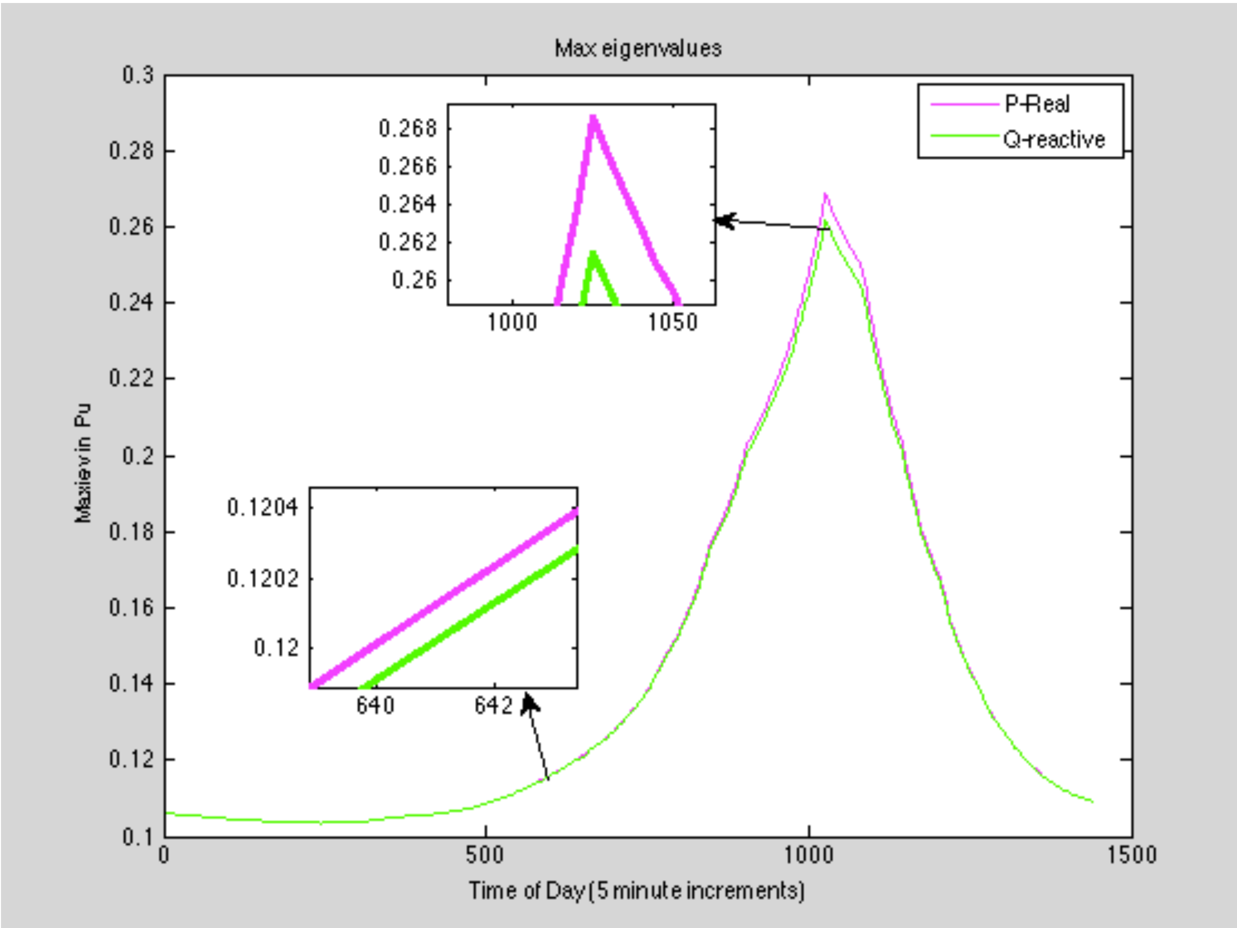

Figure 4.43 Voltage Dependent Controller (Max eigenvalues) at Bus 49, 16-gen

Chapter 5 - Conclusions and Future Work

5.1 Conclusions

In this thesis, we presented the development of a proposed framework for the implementation of the V2G concept using fuzzy logic controllers. We investigated the roles these fuzzy controllers can play in power systems as a controllable smart power flow regulators between the grid and the electric vehicles to help with the voltage stability of the grid. In this thesis a V2G system model was developed, which consists of a fuzzy logic controller, a V2G station, and a grid (16 & 6-generator test systems). The controller output was modified by taking important factors into account, such as bus voltage and electric vehicle status (SOC).

For the purpose of implementing a vehicle to grid model in this thesis, five fuzzy logic controllers are design to investigate the effect of each controller on the power system in regards to voltage system stability. The Standard On/Off Controller is designed to portray a controller with no smart rules or conditions implement to help either the grid or the EVs. What we observed in Case 1 is that the EVs simply charge until they are full no matter what status of the grid is in, hence not helping with voltage stability of the grid.

In Case 2 the Best Controller is designed to best help with the voltage system stability and meeting the SOC demand of the EVs. In Case 2 we concluded from the simulation results that the controller is performing very well in accordance to the rules implemented, also we can see that the controller favors charging a bit more than the voltage stability of the grid. Where as in Case 5 the Balanced Controller is designed to balance the needs of the EV's SOC and the grid. From the simulation results, we can see the Case 5 controller is favoring the voltage stability a bit more than the charging. The user can choose between the two controllers (Case 2 and Case 5) to best fit the needs of the users' specific design outcomes whether to favor the charging a bit more or favor the voltage stability a bit more than charging.

For the two-remainder cases, Case 3 SOC Dependent Controller and Case 4 Voltage Dependent Controller are designed to see their effects on the power system in regards to the voltage system stability if the controller is depending on only the SOC of the EV batteries or depending on the bus voltage. As seen in the simulation result we can conclude that they do not have an effect on the system voltage stability until the SOC demand and the bus voltage is fully satisfied meaning the EVs is only helping when SOC reaches (VH) and the grid is only helping with the bus voltage is at (VH).

In this thesis a study is done to determine the most effective place, weak bus vs. strong bus, for placing a V2G station. The weak and strong buses are determined based on the eigenanalysis of the loadflow Jacobian. We can conclude from the simulation results that the V2G charger is best placed on the strong bus to better help with system voltage stability of the grid.

In addition, the possibility of charging with Q (Vars) instead of P (Real power) has been examined and added to the simulation in the framework of V2G model to see if it can help with the voltage stability of the grid even more. The simulation results showed that it can help the power system in regards to voltage stability.

Lastly, all the communication between the EVs, charge stations and aggregator has been proved to be functioning properly by the simulation results. Taking all of these into account it is clear that the system is now greatly improved and has more credit in representing a real-world V2G system.

5.2 Future Work

- The contribution of a large number of EVs to balancing the power system could be investigated.
- This thesis has not considered the economic costs and benefits that might be associated with V2G, so this economical aspect of implementing V2G to a distribution system should be studied to fully realize the benefits of employing such system.
- The contribution of renewable resources like wind and solar power could be investigated to contribute in helping with the voltage stability of the system.
- Furthermore, other distribution grids could be studied. Comparing different grids can be used to improve smart charging plans.
- Design of EV chargers to provide VARs, was assumed and should be further investigated.
- The effect of station size on the magnitude of the results should be investigated. It seems intuitive that more power injected by the station would cause more significant results.

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