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# Development of a power monitoring and control system to provide demand side management of electric vehicle charging activity.

Nicholas Francis Jewell
*University of Louisville*

# DEVELOPMENT OF A POWER MONITORING AND CONTROL SYSTEM TO PROVIDE DEMAND SIDE MANAGEMENT OF ELECTRIC VEHICLE CHARGING ACTIVITY

By

Nicholas Francis Jewell
B.S.E.E., University of Louisville, 2009
M.Eng., University of Louisville, 2010

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A Dissertation Approved on

December 4, 2014

by the Following Dissertation Committee:

______________________________
Dr. John Naber, Dissertation Director

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Dr. Michael L. McIntyre

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Dr. James Graham

______________________________
Dr. Lihui Bai

DEDICATION

This dissertation is dedicated to my parents Mark and Martha Jewell. Your support and guidance throughout my life has not gone unnoticed and is greatly appreciated. I would have never imagined completing my Ph.D. without your support. I will always remember the following quote from my father as it seems to have become true over the last few months while this research work has come to a close. Whenever I would complain about not having enough time, he would always tell me:

"Remember, there are 24 hours in a day, and then there are nights."

## ACKNOWLEDGMENTS

I would like to begin by expressing my utmost thanks to my dissertation chair and mentor, Dr. John Naber, for his patience and confidence in me as I have progressed through my research. Dr. Naber has supported my endeavours by working with the University to make sure that I had the equipment and infrastructure required to complete my research. He has even taken a vested interest in the results and has purchased an electric vehicle for his personal use to assist with the needs of the project. I would also like to thank my committee members, Dr. Michael McIntyre, Dr. Lihui Bai, and Dr. Jim Graham for their input and suggestions. Dr. McIntyre has provided an inspiration to me with his work in the power electronics and EV battery systems areas. Dr. Bai provided valuable help by teaching me how to use LaTeX format for writing journal publications and this dissertation. Dr. Graham has guided me to make sure that the scope of this research was achievable and has provided significant input on the structure and revisions of this dissertation. Finally, I would like to thank the Electrical and Computer Engineering department for providing financial support for the efforts outlined in this research. This work has blazed a new path and opened up new research opportunities for future students and researchers and it would not be possible without the support provided by the department.

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## ABSTRACT

DEVELOPMENT OF A POWER MONITORING AND CONTROL SYSTEM TO PROVIDE DEMAND SIDE MANAGEMENT OF ELECTRIC VEHICLE CHARGING ACTIVITY

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Due to the recent inflow of Electric Vehicles (EVs) to the automobile market, new concerns have risen with respect to the additional electrical load and the resultant effects on an overloaded electric grid. Either for convenience purposes or possibly necessity due to limited electric range on EVs, some EV owners may desire to charge their EV while at work in addition to charging at home. These forward-thinking daytime charging providers are typically Commercial and Industrial (C&I) electric ratepayers, or other large electric consumers which constitute the majority of businesses, shopping centers, academic campuses and manufacturing facilities. Increased electricity consumption due to EV charging activity results in higher electricity costs due to differences in the billing structures between residential and C&I electric ratepayers. Therefore, it is beneficial to the EVSE charging provider to minimize charging activity around peak demand periods which would result in lower electrical costs overall. A solution is developed that can provide this control without creating a

nuisance to electric vehicle owners since EV charging demand is somewhat inelastic due to range anxiety. The primary objective of the research detailed in this dissertation is to develop a novel demand side management system for monitoring the peak demand of commercial time-of-day electric ratepayers that cost effectively predicts and controls electric vehicle charging during peak demand periods. This objective is achieved, therefore confirming the hypothesis that such a system can provide cost and demand benefits to forward-thinking commercial electric ratepayers that provide daytime charging capabilities.

This work proposes and evaluates a novel Power Monitoring and Control System (PMCS) that can be implemented at C&I EV charging locations to minimize or eliminate the negative impacts of charging electric vehicles at the workplace in C&I environments. Operation of the PMCS begins by forecasting electrical demand in advance of every 15 minute demand interval throughout the day. The forecast is generated using an artificial neural network and a number of input data streams. Electrical demand has been shown to correlate well with weather data such as temperature and dew point. Therefore, using those measurements along with a date and time stamp, and historical electrical demand measurements, a highly accurate forecast for the following 15-minute demand interval was achieved. From that forecast, the number of EV charging stations that may be active, without the chance of creating new electrical demand peaks, is calculated. Finally, the forecast is then used to properly schedule EV charging activity so that electrical demand peaks can be avoided but charging activity is maximized. The avoidance of charging activity at or near peaks in electrical demand results in lower total electric costs associated with the charging process. The final design was implemented in an EV charging testbed at the University of Louisville and data was collected to verify the operation and performance of the PMCS.

With a properly designed scheduling and prioritization control algorithm, increases in electrical demand and associated costs are limited to the error in the forecasting algorithm used for predicting electrical demand levels. The final design of the forecasting algorithm results in a mean absolute percent error of 0.02% to 0.08% in the electrical demand forecast. This corresponds to approximately 3 to 10 kVA of error in electrical demand. Taking this error into account, total cost of charging several EVs is reduced by nearly 90%. Furthermore, for scenarios where there are several more electric vehicles requiring charge than there are charging stations available, several scheduling algorithms are presented in an attempt to minimize the total processing time required for completing all charging transactions.

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# CHAPTER I
# INTRODUCTION

This dissertation is based on the design and development of a novel Power Monitoring and Control System (PMCS) for Plug-In Hybrid Electric Vehicle (PHEV) and Battery Electric Vehicle (BEV) charging applications. The system described within provides demand management of PHEV charging loads for commercial and industrial time of day electricity ratepayers. Commercial and industrial time of day ratepayers include shopping centers, schools, businesses, and factories that typically consume very large electrical loads of between 250 kVA and 50000 kVA [1].

Typically, demand response programs are implemented at the utility level and require significant communications infrastructure between the utility and the electric consumer. These programs either directly control loads through remotely controlled switches or offer financial incentives to the electric consumer to change power consumption patterns. The PMCS described here is a special case of demand management since the commercial ratepayer (The University of Louisville) acts as an intermediate entity between the utility and the electric vehicle owner as shown in Figure 1. Demand management provided by the PMCS occurs between the electric consumer and the auxiliary PHEV charging load. In Figure 1 blue arrows represent traditional implementation of demand side management, red arrows represent demand management provided by PMCS. The PMCS provides benefits of demand reductions for both the electric utility and the commercial ratepayer. Additionally, the commercial ratepayer benefits from significant cost reductions for electricity consumed. The figure represents the relationship between the utility, the commercial electric consumer, and the EV owner.

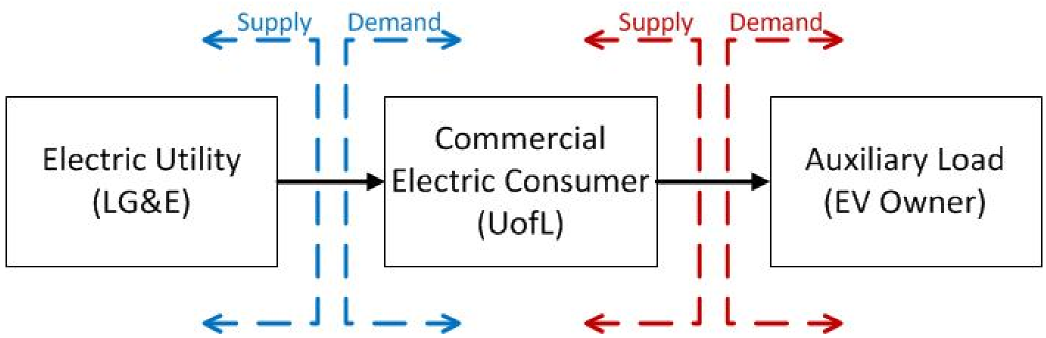



FIGURE 1: Supply and demand structure between utility, commercial entity and auxiliary load.

As PHEVs grow in popularity, the installation of charging infrastructure at the workplace becomes an inevitable requirement to avoid range anxiety [2], which is commonly associated with electric vehicles. Studies have shown that concentrated PHEV loads on the US power grid can have large impacts on the load profile in that region [3]. The increased power system load can potentially impact the reliability of the power system when the grid operates near its maximum capability for extended periods [4]. However, intelligent PHEV charging systems that predict these adverse grid conditions can prevent these negative impacts by scheduling and dispatching charging activity accordingly.

The following novel power monitoring and control system is proposed. The PMCS shown in Figure 2 provides a central communication and control system for the PHEV charging infrastructure, PHEV loads, and utility metering devices. It provides an interface to the smart grid so that intelligent decisions can be reached regarding the control of charging activity. The PMCS allows PHEV charging loads to be intelligently scheduled so that charging activity during the peak demand periods is reduced or eliminated when possible to minimize the electricity costs from a large scale deployment of PHEVs.

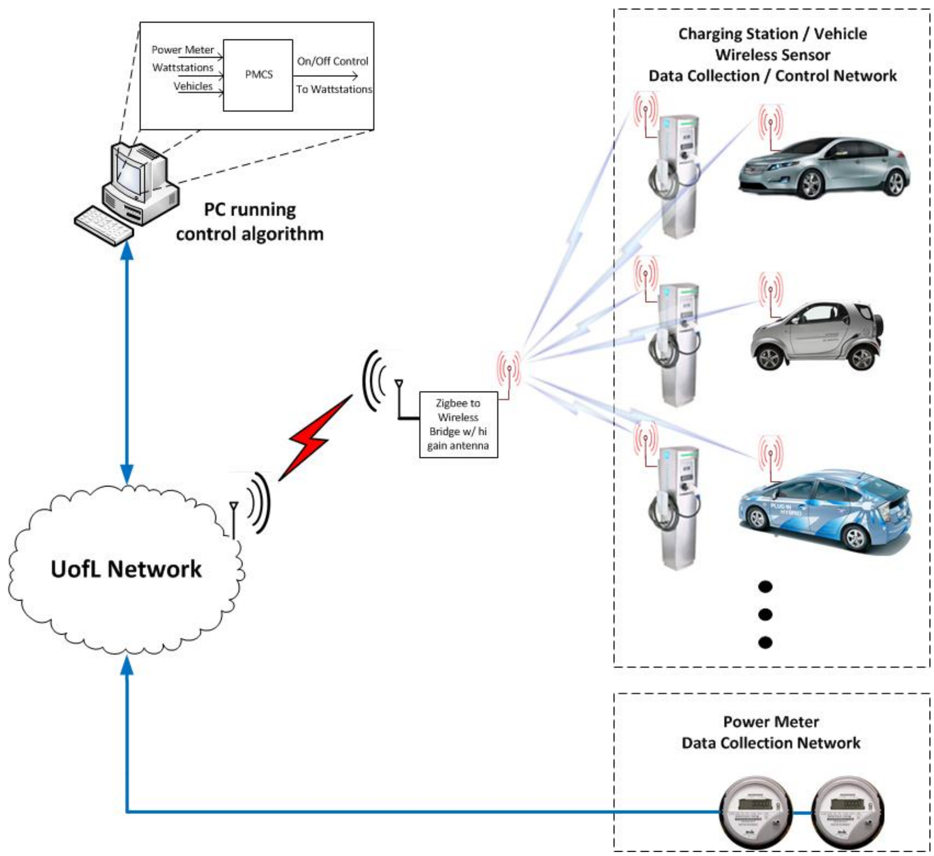



FIGURE 2: Proposed network topology of PMCS for controlling charging activity.

A peak electrical demand prediction algorithm is included within the PMCS design that will be used to determine the number of PHEVs that can charge during the subsequent demand interval without the possibility of driving the demand level to a new peak. Real-time data collection from the utility meters, PHEV battery systems, charging stations, and other smart grid enabled devices will allow the system to make intelligent decisions regarding how to manage charging loads. The overall design of the PMCS can be subdivided into a number of elementary modules as shown in Figure 3.

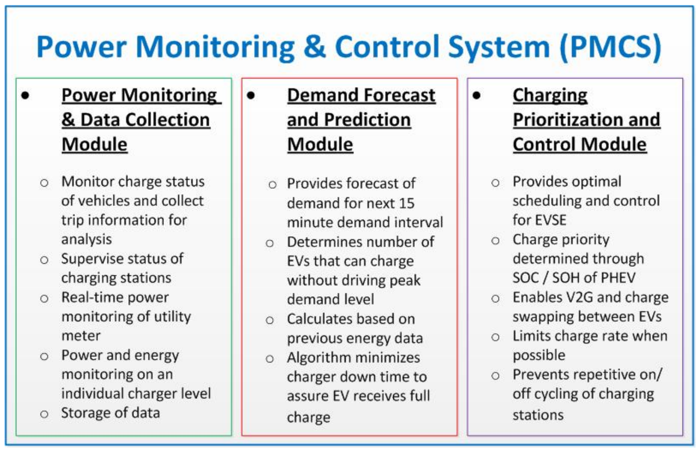



FIGURE 3: 3 primary modules that form the PMCS.

The first module of the PMCS is responsible for real-time data collection from a variety of sources. This module communicates with the customers utility meter to collect energy and power data that is used by the forecasting algorithm. It also communicates with the charging stations to determine energy usage and charging status. Finally, it also communicates with the electric vehicles to determine State Of Charge (SOC) and State Of Health (SOH) of the vehicles battery systems. Data storage is provided by the data collection module for historical data trending that is used to further refine the operation and performance of the PMCS throughout its lifetime.

One primary obstacle that must be overcome for this system to work properly is the unpredictability of the consumers energy load profile and the associated demand peaks. Electrical loads on a large micro-grid tend to be unpredictable and non-linear. The second module of the PMCS provides peak prediction and forecasting which is utilized to determine the number of EVs that are allowed to charge during the next 15 minute demand interval. The forecasting algorithm predicts these electrical demand peaks in advance by processing historical data and current demand trending.

The third major module of the PMCS provides charging prioritization and control. In the event that the forecasted number of vehicles allowed to charge in the subsequent demand window is less than the number of vehicles connected, a charging priority is determined and specific charging stations are temporarily disabled or charging is slowed until the forecast allows for more vehicles to charge. Charging priority is given to EVs with lower SOC over vehicles with higher SOC in an attempt to create a fair and impartial charging environment. Figure 4 provides a summary of the process flow followed by the PMCS. The charge scheduling and prioritization module is shown on the right-hand side of the decision diagram and is enabled in events where charger availability is less than the total number of electric vehicles requiring charge.

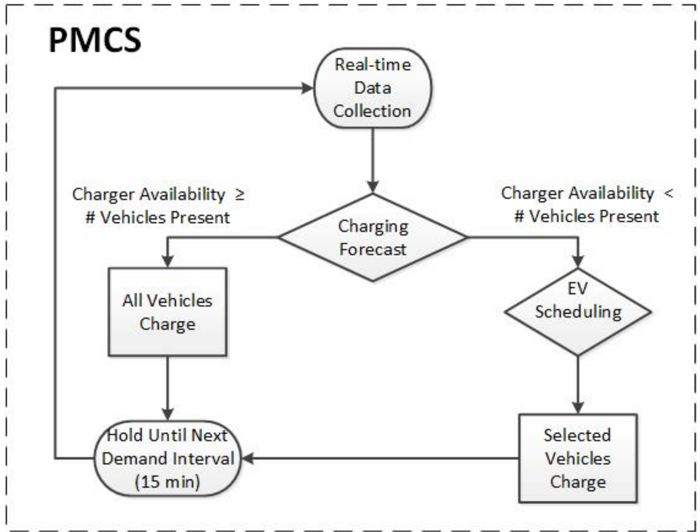



FIGURE 4: Decision diagram of PHEV demand management system.

Intelligent control of PHEV charging loads not only provides benefits to utilities due to reduced demand load but it also provides significant cost reductions to the commercial or industrial electric consumer where the PHEV infrastructure is installed [1]. Currently, only a handful of states allow for the resale of electricity once it has been sold by the electric utility to an electric consumer. This creates a problem in many states, including the state of Kentucky, since the owner of PHEV charging infrastructure in the state cannot bill users for electricity consumed during the charging process. The PMCS described here will significantly decrease electricity charges by scheduling charging activity therefore limiting the disincentive to the adoption of PHEV charging infrastructure. A detailed explanation of commercial and industrial time of day billing structures will be presented in the background information section of this dissertation to provide evidence as to the cost savings that are possible with such a system.

## A. Dissertation Structure

This dissertation will begin by providing a detailed problem statement. After discussing the purpose and importance of the study, a list of specific objectives will be presented. These objectives will define the scope of the study and will provide the outline of the work described within this dissertation. Following the presentation of the project objectives, an in-depth review of prior art will be offered. The literature review will present germane publications that address both studies that are directly and indirectly related to the topics proposed here.

Next a detailed background of the problems associated with large deployments PHEV charging infrastructure in commercial and industrial environments will be presented. The background will better inform the reader about the issues at hand and will establish the need for a solution. Further, background information will be provided to enlighten the reader about PHEV charging stations, electricity demand, demand response programs, and commercial time of day billing structures. Following the background information, the research methods required to complete the objectives listed will then be presented.

Finally the design and operating principles of the PMCS and associated hardware will be documented and detailed thoroughly. This includes a study of various control methods and algorithms considered, options regarding network topology, and hardware developments required throughout the implementation process. The dissertation will conclude by presenting data collected from the control system and will provide evidence of cost savings and demand benefits achieved by the proposed design.

## B. Problem Statement

Electric vehicle charging for commercial or industrial electric ratepayers is not scalable due to resultant increases in electricity demand peaks and associated communication costs, which will significantly increase the total cost of charging. Charging activity coincident with demand peaks can result in even a small number of charging stations impacting the monthly electrical demand peak therefore resulting in significant increases in electrical costs. The increase in electric costs due to electric vehicle charging activity in C&I environments results in a substantial disincentive to EV adoption on a large scale.

Electric vehicle charging capabilities at the workplace, or in commercial or industrial environments, is detrimental to the adoption of electric vehicles due to new electrical demand peaks in the load profile and higher electric costs resulting from the charging process. Increased demand peaks result in additional electrical costs which directly affects fuel costs associated with ownership of an electric vehicle. A solution is required to prevent this disincentive.

Table 1 demonstrates the costs associated with uncontrolled PHEV charging for C&I time of day electric ratepayers. Equations used to calculate the charges listed in the table are outlined in the background information section of this dissertation. Table 1 suggests a vastly different impact on electric customers under residential and C&I rate structures. In particular, C&I ratepayers could pay up to four or five times the cost of charging at typical residential rates for an equivalent amount of energy. These costs were calculated for both residential and C&I electric ratepayers

TABLE 1

Calculated cost of uncontrolled charging activity based on 2014 LG&E electric rate structures [1].

| Number of EVs | C&I Energy Cost Increase | C&I Demand Cost Increase | C&I Total Cost Increase | Residential Cost Increase |
|---|---|---|---|---|
| 1 | \$5.49 | \$50.14 | \$55.14 | \$12.38 |
| 10 | \$54.91 | \$501.35 | \$556.26 | \$123.78 |
| 100 | \$549.12 | \$5,013.50 | \$5,562.62 | \$1,237.85 |
| 1000 | \$5,491.20 | \$50,135.00 | \$55,626.20 | \$12,378.50 |

[1], although regulations against high energy consumption for residential ratepayers normally prohibit such activity. The energy and peak demand cost increases were calculated for various numbers of EVs introduced using a worst case scenario, where EV charging is uncontrolled and the resultant increase in demand from EVs occurs during the peak demand window. This figure is an estimate only and will vary for specific communities with different rates and rate structures. However, it proves the significant impact EV charging can have on C&I consumers. Approximately 90% of the total electricity cost is due to the peak demand cost which creates a great disincentive for large scale EV adoption [5][6]. A number of assumptions are made when calculating the values represented in Table 1. These include that EVs require average of 8kWh of charge per day and are charged during 21 working days per month. In order to show the maximum impact, charging activity is coincident with peak in demand profile.

In addition to the extra cost of charging PHEVs due to time of day rate structures, the added load during peak demand periods creates reliability issues for the electric utility. Figure 5 shows the effects caused by the charging activity required for 100 electric vehicles added to the University of Louisville electrical demand profile. Resultant increases in demand are detrimental to the utility and the electric ratepayer. The solution presented in this dissertation only addresses demand response for EV charging to reduce peak demand charges and limit strain on the utility during peak demand periods, but could also address grid instability as a beneficial indirect result.

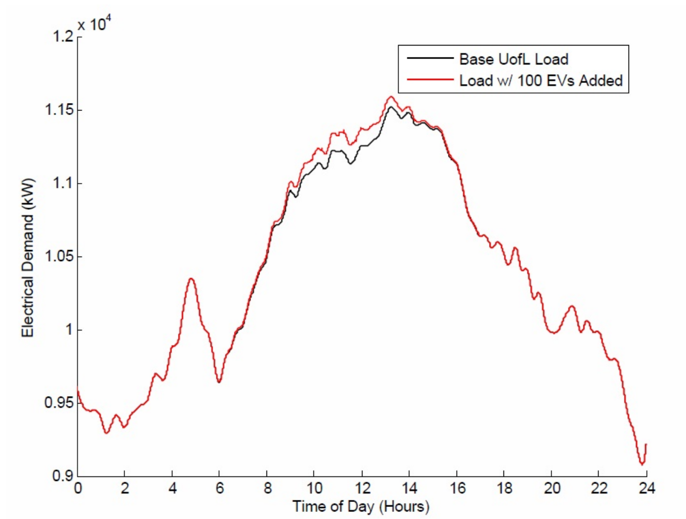



FIGURE 5: Electrical demand profile measured at University of Louisville with 100 EV charging load added.

## C. Research Scope and Objectives

The primary goal of this research and project is to demonstrate a novel power monitoring and control system that provides demand response capabilities for electric vehicle charging infrastructure in commercial time-of-day electricity markets. The proposed system will benefit the electric utility and the electricity consumer by controlling charging activity and eliminating the possibility of demand peak increases that could result. This system will provide modular communication and control capability between the vehicles, the charging stations (EVSE), the utility meter, and other upstream control systems or energy management systems including the "smart grid".

The underlying infrastructure provided by the proposed power monitoring and control system will provide the base working platform needed for future technologies such as Vehicle-to-Grid (V2G) charge sharing, grid storage, and peak load leveling. This assumes the required technologies are developed and integrated into the electric vehicles of the future. Considerations will be made in the design to account for the integration of renewable sources to the system. A unique internet user interface will be developed for web enabled smart phones or computers that will allow users to customize charging options, view consumption data, and analyze driving patterns.

As part of this research, existing EVSE control systems and current demand response programs will be examined and studied to determine the optimal control strategy for the commercial time of day ratepayer, the EV owner, and the utility. A detailed list of desired objectives is provided here.

- Develop a novel demand side management system for monitoring the peak demand of commercial time-of-day electric ratepayers that cost effectively predicts and controls electric vehicle charging during peak demand periods.

- Establish optimal forecasting and control strategies to manage inelasticity of EV charging while still providing least electric cost and best demand benefits. Minimize forecasting error to prevent potential errors from driving electric costs.

- Formulate a prioritization algorithm by using vehicle state of charge for scenarios where charging activity must be disabled.

- Propose an optimal scheduling algorithm for cases where the ratio of EVs requiring charge to EVSE availability is greater than 1.0 (i.e. more vehicles than charging infrastructure available).

- Minimize IT installation and operating costs associated with communications and networking.

- Study and implement cyber security measures to protect the control system and user information.

- Implement the designed power monitoring and control system developed in the first objective at the University of Louisville.

- Collect and analyze energy consumption and electric cost savings data to evaluate performance of the system.

- Provide a user interface to provide supervisory power monitoring and control of the PMCS and EVSE infrastructure.

- Deliver EVSE availability and location information to EV owners through the user interface.

- Provide system summary including utilization, costs, energy consumption and charging behaviors to electric ratepayer (UofL).
- Alert users and system administrators when peak demand events occur and charging is disabled.

The approach for achieving these objectives and PMCS design details are provided in chapters III through VI of this dissertation.

A hypothesis can now be formed regarding the expected behavior of the control system proposed. An accurate forecast of electrical demand with minimal (i.e. less than 1%) error, along with an adequate scheduling algorithm, will allow for EV charging activity to commence without driving electrical demand peaks and keeping additional electric costs at a minimum. This results in acceptable electrical costs therefore limiting the disincentive to EV adoption that is currently present for charging activity under commercial and industrial electric rate structures. This hypothesis will be confirmed through proper design of the forecasting and control algorithms required along with simulation and practical testing of the overall solution.

## D. Purpose and Importance of Study

Concerns over Greenhouse Gas (GHG) emissions have slowly risen over the past years as increasing numbers of vehicles are driven on roadways throughout the world. Figure 6 shows a nearly 33% increase in GHG emissions for automobiles over a 16 year span from 1990 to 2006. Auto makers have turned to alternatively fuelled vehicles in an attempt to help appease these concerns regarding GHG emissions. The fastest growing market for alternatively fuelled vehicles is for plug-in hybrid electric vehicles as these minimize tailpipe emissions and move the burden of GHG emissions away from the automobile and towards electric generation facilities.

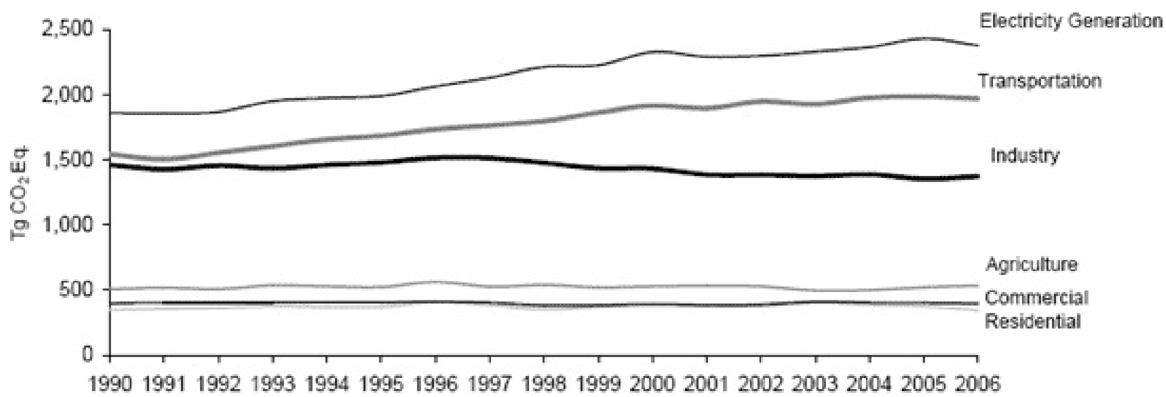



FIGURE 6: Greenhouse gas emissions by sector (1990 - 2006) [7].

Due to this recent inflow of plug-in electric vehicles to the US automobile market, the need for public EV charging infrastructure has risen as well. The limited electric range of PHEVs results in the need to charge the EV batteries away from home. Researchers have recognized the problems associated with the additional electric load due to EV charging. The majority of these researchers focus on the global aspects though and look at the impacts on the power grid as a whole. This work focusses on a more localized problem that may be a limiting factor to the widespread adoption of EVs. The cost of charging electric vehicles varies greatly depending on where and when the charging activity takes place. This cost, and the overall effects on the power grid, can be minimized by implementing an intelligent charging control system.

This study aims at the successful development of a power monitoring and control system that provides demand management of PHEV charging loads for commercial and industrial time of day ratepayers. The United States Government has been working to reduce greenhouse gas (GHG) emissions for the last 40 years. The most recent goals aim at reducing these emissions by 60% to 80% of levels measured in 2005 by the end of 2050. The transportation sector has been the fastest growing source of GHG emissions and accounts for nearly 27% of the total GHG emissions in the United States [8]. The reduction of GHG emissions can only be realized if alternative fueled vehicles become widely accepted. Figure 7 shows that for the transportation sector alone, light duty vehicles account for nearly 63% of the total GHG emissions.

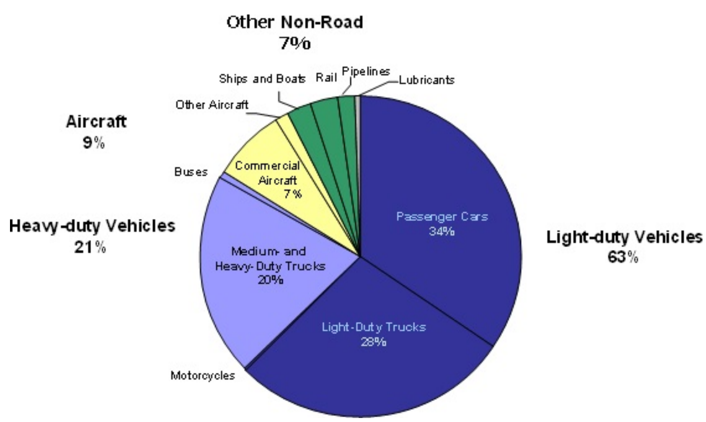



FIGURE 7: U.S. Transportation Greenhouse Gas Emissions by Source, 2006 [7].

Much to the delight of government policymakers, electric vehicles and hybrid variants have gained popularity in the past years as acceptable options for limiting GHG emissions. In a recent report by the US Department of Energy, workplace charging capabilities have provided over 6.7 million kWh of electricity annually, which saves more than 800,000 gallons of gasoline and 5.5 million pounds of GHG emissions per year [9]. However, as the popularity of these vehicles continues to rise as shown in

Figure 8, problems arise for electric utilities as the increased electric demand strains an already overloaded US power grid. Intelligent management of charging activity for these electric vehicles is required to prevent this negative impact.

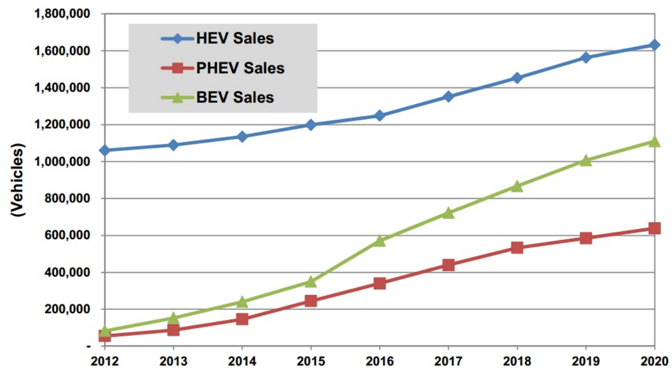



FIGURE 8: Electrified vehicles sales by segment, world markets 2012-2020 [10].

Additionally, as the number of electric vehicles on the road increases, the need for public charging infrastructure becomes a necessity in addition to residential EV charging infrastructure already installed at the home. Installation of EVSE at the workplace is necessary to overcome range anxiety and other range issues associated with electrified vehicles. The cost of electricity can vary greatly due to demand charges faced by commercial time of day ratepayers; therefore a control system to intelligently schedule PHEV charging is needed to minimize costs. A properly designed control system can also provide benefits to the electric utility by reducing peak demand and minimizing the potential for grid overload emergencies.

## E. Design Method

The Power Monitoring and Control System (PMCS) described within operates as an integrated system designed to provide demand management of electric vehicle charging infrastructure for commercial time-of-day electric consumers. This system prevents PHEV charging activity from driving the demand level for a given consumer to a higher peak level. Using quantities that are easily measurable such as time of day, present electrical demand, outside temperature, etc, an accurate demand forecast can be developed from which control decisions can be based. Individual vehicle charging is disabled or slowed when demand peaks are encountered. By restraining the charging load, electricity demand from the utility is reduced and therefore cost of charging is minimized for PHEV owners or EVSE providers.

Wireless communication bridges will be used to provide communication between the various system components including the vehicles, the charging infrastructure, the utility meter and other energy management systems including the smart grid. ZigBee is the preferred wireless communication protocol due to its acceptance in the smart grid industry for communication applications and low power consumption. However, other communication protocols will be considered throughout the design.

## F. Review of Prior Art

The increasing popularity of electrified vehicles as alternatives to traditional internal combustion engine powered vehicles has presented numerous issues across the electric grid. Studies show that the grid can support a large number of these vehicles; however, charging activity must take place at night or during off-peak hours to prevent grid overloading issues [3]. Range anxiety is a true limiting factor to the widespread roll out of PHEVs into the US vehicle fleet. Current battery technologies and vehicle designs allow for limited range on a full charge. Drivers with longer daily commutes may not have adequate range to complete all of their daily driving requirements without charging throughout the day or during peak demand periods. Therefore, a solution is required to intelligently control charging activity near and during peak demand periods throughout the day. Such a system would provide benefits to both the electric utility through reduced peak loads and to the electricity consumer by reducing electric rates paid for a given quantity of energy consumption.

Existing control systems have been designed to limit a vehicles charging until off-peak hours, however these systems assume charging activity occurs at the home only [16]. Charging at the workplace or in the middle of a trip is sometimes inevitable due to the driving range required. This poses a problem in that most businesses, factories, schools, and shopping centers are considered commercial electricity consumers due to the quantity of their electric demand and therefore are billed for electricity consumption on a time-of-day rate schedule. This variable cost of electricity creates a non-scalable model for PHEV charging.

This section reviews important and novel research and development that has contributed to the field of demand management and electric vehicle charging. Relevant literature was found from the following databases: IEEE Xplore, ISI Web of Knowledge, Google Scholar, and Minerva Journal Finder. Search terms included permutations and combinations of the following: electric vehicle (EV), PHEV, charge control, demand, demand management, EVSE, charging station, demand forecast. Additional literature was located by cross-reference. The prior art presented here is split between studies that are directly and indirectly related to the topic of this dissertation.

### 1. Studies Directly Related

There are a number of publications available in scholarly journals pertaining to the control of electric vehicle charging to reduce demand on the electric grid that are directly related to the work outlined in this research. All of these publications are based on the fact that uncontrolled charging activity can lead to immense problems with the electric power grid without proper supervisory control. The majority of publications found focus strictly on time-of-day charging or dynamic pricing in deregulated energy markets while others focus on charging control based on renewable energy availability. This section will detail studies that are directly related to the research and design proposed in this dissertation. Directly related works of art are subdivided into: time-of-day charge control, charge control based on variable energy pricing, charge control to provide ancillary services, and algorithms and demand forecasting algorithms. The first three relate to this work as a whole and the latter relates to a subsection of this work.

## Time Shift or Time-of-Day

Table 2 provides a summary of prior art discovered that relates to simple time shift or time-of-day charge control strategies. The earliest example of PHEV charging control was presented by G.T. Heydt in 1983 [11]. Heydt recognized that by shifting charging loads from peak times to off-peak times, the load factor of the power grid is greatly improved. This control was based on a simple time of day strategy that disabled charging during specific time periods. Analyses were performed on the subsequent cost of energy and the potential health benefits provided to transformers. The study concluded that with load management and the shifting of loads to off-peak periods, the load factor can be improved and additions to grid infrastructure are not needed. This is a valuable work in that it shows the importance of demand side management of electric vehicle charging activity in order to reduce cost of electricity per-unit and minimize potential effects on load factor and how that can affect the distribution grid.

There is a long break in prior art from Heydt's research to more recent research that is most likely due to the lack of electrified vehicles in the automobile market during that period. However with emerging concerns regarding greenhouse gas emissions, air quality, and improved vehicle mileage, auto manufacturers have begun developing new electric drive or plug in hybrid electric drive vehicles. With recent developments such as the Chevrolet Volt [12], Nissan Leaf [13], Tesla [14], Toyota Prius [15] and

TABLE 2: Summary of prior art utilizing time-of-day or time shift charging.

| **Date** | **Primary Author** | **Charge Control Method** | **Title** |
|---|---|---|---|
| May-83 | G. T. Heydt | Time of day | The Impact of Electric Vehicle Deployment on Load Management Strategies [11] |
| May-07 | K. Parks | Residential Time of day | Costs and Emissions Associated with Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory [16] |
| Aug-11 | N. Saker | Direct Load Control / Time-Shift | Electric Vehicles Charging Scenarios Associated to Direct Load Control Programs (DLC) [17] |
| Dec-11 | T. Lyon | Time of day | "Is "Smart Charging" Policy for Electric Vehicles Worthwhile?" [18] |
| Jan-12 | H. Yano | Time of day | A Novel Charging-Time Control Method for Numerous EVs Based on a Period Weighted Prescheduling for Power Supply and Demand Balancing [19] |
| Mar-12 | U. Reiner | Time of day | Distributed Self-organizing Electric Vehicle Charge Controller System: Peak Power Demand and Grid Load Reduction with Adaptive EV Charging Stations [20] |

others, more emphasis has been focused on the potential negative grid impacts that EV charging demand can create. Other research has built upon Heydt's studies by further developing time shift strategies for PHEV charging [16], [17], [18], [19], [20].

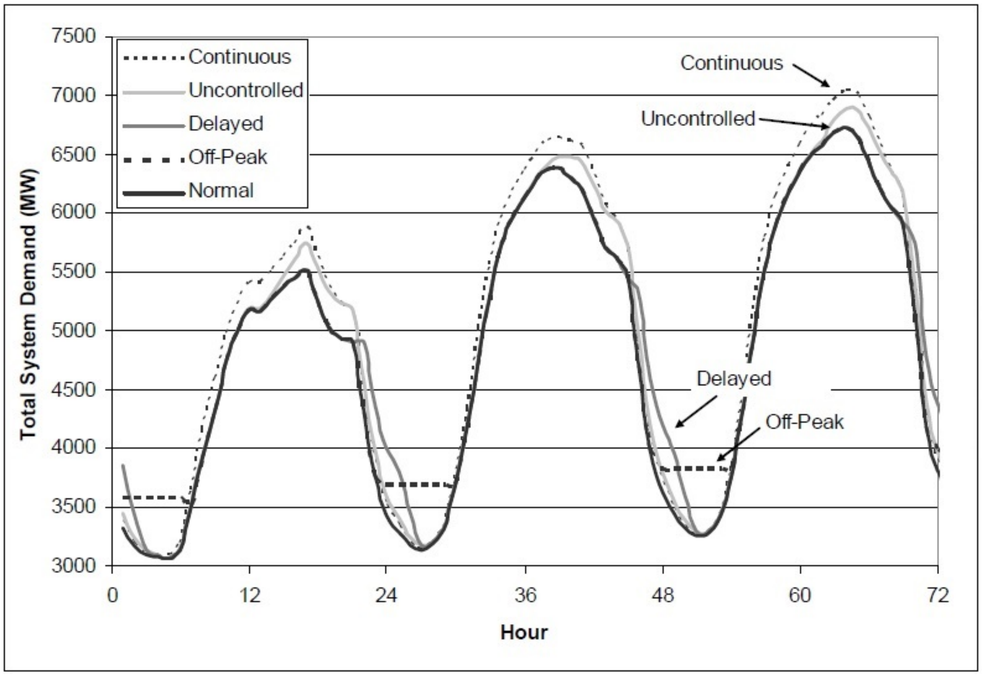



FIGURE 9: Summer demand for Colorado utility with and without control [16].

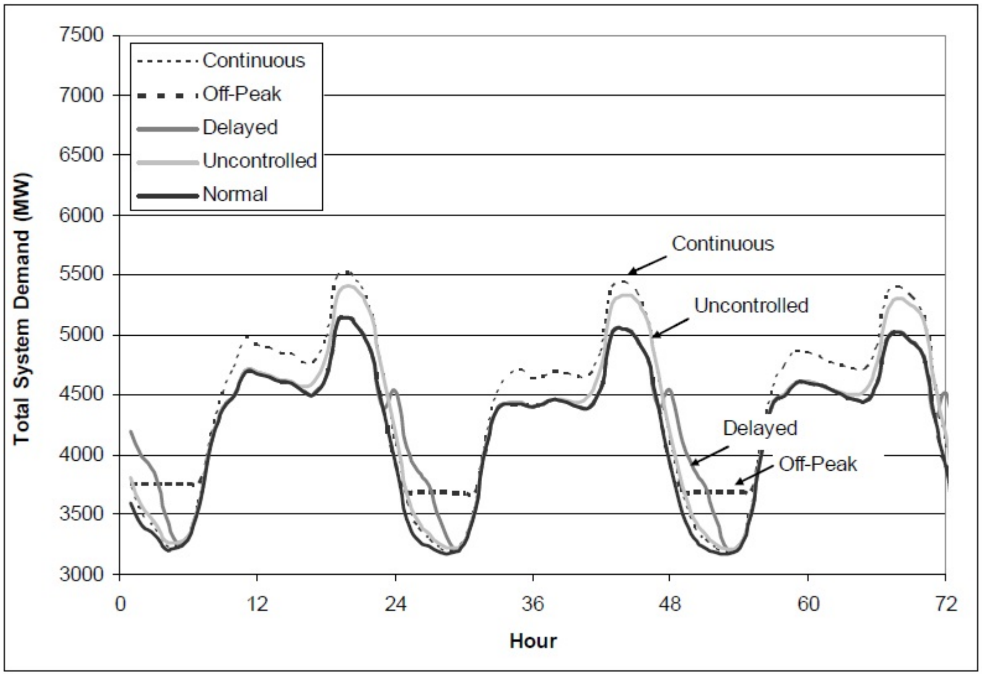
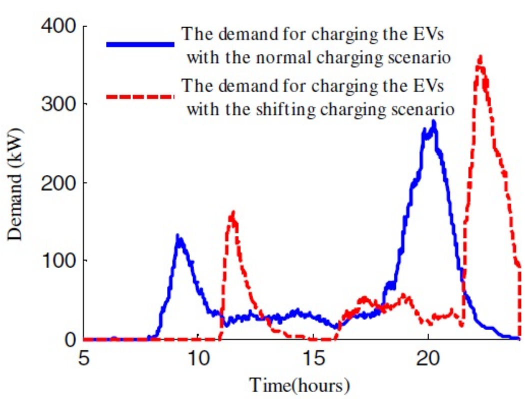



FIGURE 10: Winter demand for Colorado utility with and without control [16].

In a report by the National Renewable Energy Laboratory (NREL) [16], it is noted that extra generation capacity is not required if all charging activity is shifted to off-peak periods as shown in Figures 9 and 10. These plots show the resultant demand for uncontrolled, delayed, and off-peak charging scenarios. Parks et al. (NREL) examined the effects of EV charging activity on the electric utility, specifically a local Colorado utility. The study concluded that the addition of uncontrolled EV charging activity would result in the need for additional generation capacity, however controlled charging would eliminate that need. EV charging activity would also affect emissions from electricity generation due to the generation mix utilized at various periods of the day. Finally, the cost of charging was examined based on the time-shift implemented. Moving charging to off-peak periods resulted in cheaper generation costs due to the generation mix utilized by the utility at that time.

In another study by N. Saker et al. [17], the author realizes that most charging activity occurs in three primary distributions. These are modeled as uniform distributions in the morning, afternoon and evening. When added to the existing demand profile of the electric grid, early evening charging creates a new demand peak. As a solution, two different options are studied. The first is a simple time shift in charging is enacted that simply shifts the charging load a fixed time period. This solution lessens the impact on the peak grid demand but also has the possibility of creating new local peaks in the demand profile. The second option proposed is to divide the vehicles in each of the three distributions (morning, afternoon, and evening) into three equal subgroups each. This "three steps charging" method shifts a portion of each charging distribution by +/- a standard deviation to help smooth the additional load profile. Figure 11 shows the results of the time shift and three steps charging control methods studied.



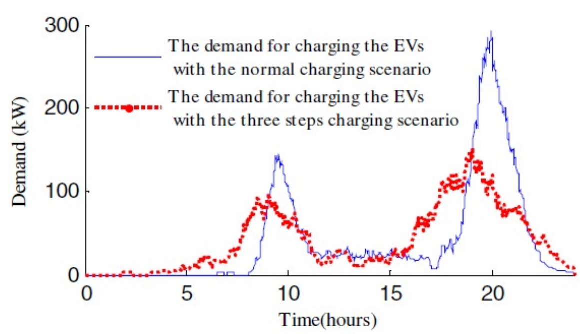




FIGURE 11: Simulation results showing time shift and three steps charging control methods [17].

T. Lyon et al. [18] point out that significant reductions in electrical costs can be realized though time shifting EV charging activity as well. These costs are only a small percentage of total electric costs though, which vary from market to market. The implementation of time-of-use pricing is also studied. However, the savings are outweighed by the cost of the smart grid infrastructure required for controlling charging activity and providing the information required to implement time-of-use rates.

In residential cases, it is easy to shift EV charging demand since the vehicle is parked the majority of the time and is often plugged in throughout the entire off-peak period. The majority of studies enacting a time-shift control method for EV charging assume the residential scenario where the vehicle is parked at the charger for extended periods of time. Figure 12 shows another example of the possible benefits of using a time-shift for scheduling PHEV charging activity. From the multiple studies discovered, time shifting is the simplest and most inexpensive demand response solution. Benefits of such a control scheme include better utilization of energy generation and the reduction in need for additional peak capacity at generation plants. Grid disturbances, such as voltage sags or frequency deviations, can also be minimized by enacting time-based charging controllers [20]. In residential scenarios where all charging occurs at the home and daily driving patterns can be completed without the need to recharge during the day, time shifting is an acceptable control method to minimize grid impacts. However, there are disadvantages to such a simple solution. Time shifting of charging activity to off-peak periods is not always a viable option due to electric vehicle range and charging throughout the day is inevitable. Additionally, shifting charging activity can also affect greenhouse gas emissions due to differing generation mixes at various periods during the day.

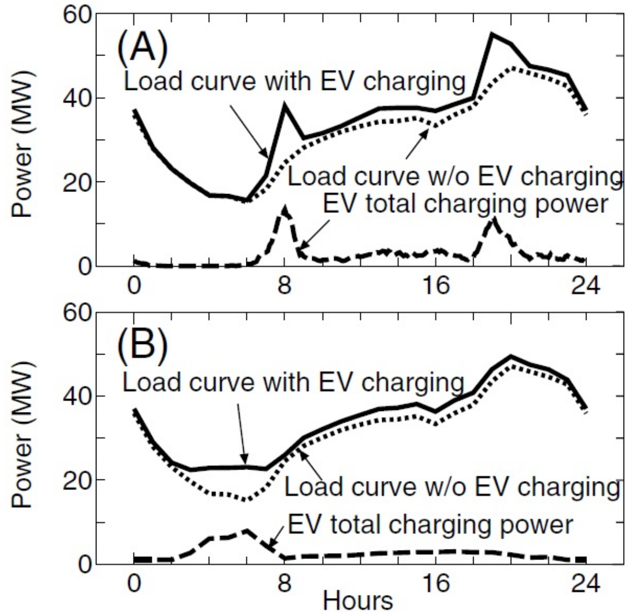



FIGURE 12: Example of time shifting PHEV charging loads to off-peak hours [19].

TABLE 3: Summary of prior art utilizing variable pricing as control method.

| **Date** | **Primary Author** | **Charge Control Method** | **Title** |
|---|---|---|---|
| Nov-08 | M. Galus | Demand response, Var. Pricing | Demand Management of Grid Connected Plug-in Hybrid Electric Vehicles [21] |
| Aug-11 | N. Rotering | Var. Pricing | Optimal Charge Control of Plug-in Hybrid Electric Vehicles in Deregulated Energy Markets [22] |
| Jan-12 | S.S. Raghavan | Direct Load Control, Var. Pricing | Impact of Plug-in Hybrid Electric Vehicle Charging on a Distribution Network in a Smart Grid environment [23] |
| Jan-12 | D. Ban | Var. Pricing | Demand Response Control for PHEV Charging Stations by Dynamic Price Adjustments [24] |
| Feb-12 | M. Rastegar | Direct Load Control, Var. Pricing | Load Commitment in a Smart Home [25] |

Continued on next page

TABLE 3 – continued from previous page

| **Date** | **Primary Author** | **Charge Control Method** | **Title** |
|---|---|---|---|
| Apr-12 | P. Finn | Demand response, Var. Pricing | Demand Side Management of Electric Car Charging: Benefits for Consumer and Grid [26] |
| Aug-12 | P. Sanchez-Martin | Direct Load Control, Var. Pricing | Direct Load Control Decision Model for Aggregated EV Charging Points [27] |
| Sep-12 | Z. Fan | Demand response, Var. Pricing | A Distributed Demand response Algorithm and Its Application to PHEV Charging in Smart Grids [28] |

## Variable Pricing in De-regulated Markets

In an attempt to solve the problems associated with simple time shifting control of PHEV charging, more recent studies have used dynamic energy pricing to optimize charging patterns [21], [22], [23], [24], [25], [26], [27], [28]. Table 3 provides a summary of prior art discovered relating to EV charge control strategies based on variable pricing signals. In de-regulated energy markets, dynamic pricing can be used to account for fluctuations in electrical demand and generation capacity. These fluctuations include: peaks when generation capacity is near exhaustion, lack of generation capacity, and excess generation during low demand periods. Typically, pricing signals are used either in real-time to make control decisions on the spot, or pricing signals are used to predict future energy costs to help with scheduling charging activity and energy consumption. Figure 13 shows how price-based and incentive-based demand response fit in for various time scales utilized by forecasting and control systems.

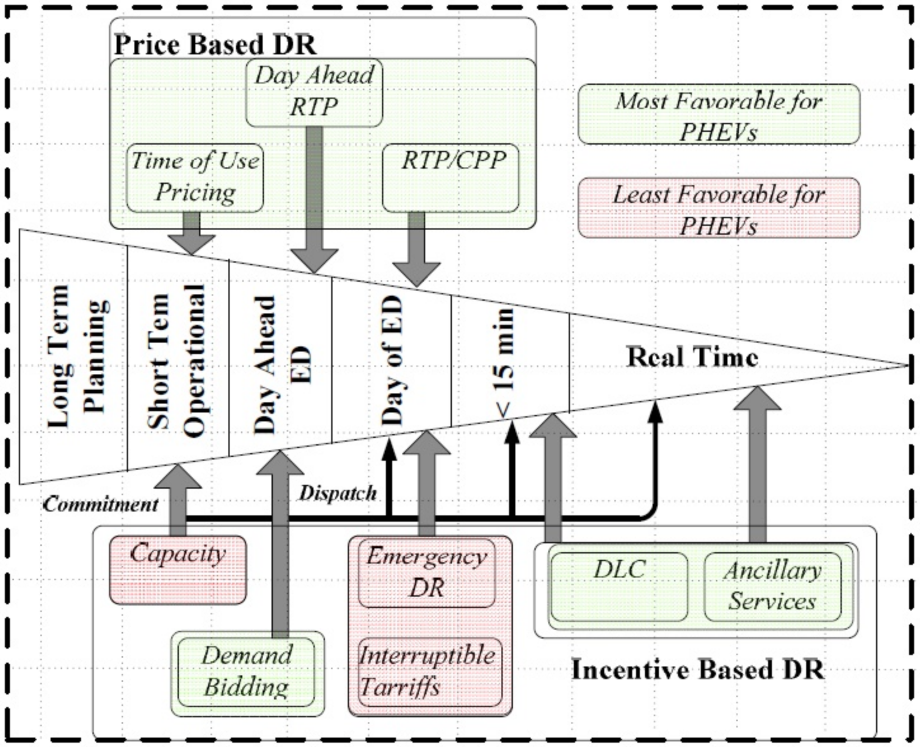



FIGURE 13: Commitment and dispatch timescales and the role of PHEVs for DR [23].

In most works published in this area, pricing signals are used directly in real-time to affect charging behavior. M. Galus, et al. proposes a multi-agent based approach to controlling EV charging [21]. Dynamic pricing structures are incorporated to reduce EV charging demand during peak periods. Pricing signals are sent to the energy hub and made available to the EV owner. A personal value factor is utilized to allow the EV owner to specify how much they are willing to pay for electricity. Similarly, in work performed by Z. Fan, et al., variable pricing techniques are adapted from congestion pricing in internet traffic control [28]. Figure 14 shows the variable pricing structure used. The more energy that is consumed, the higher the rate or total energy cost that is paid, which is similar to internet congestion pricing. This research assumes that each EV owner generates a willingness to pay (WTP) parameter. This value represents the max rate the user is willing to pay for electricity consumption. Charging time slots are then scheduled and charging rates are modified based on dynamic pricing signals and the WTP parameter specified by the EV owner. The system operates by allowing those that are willing to pay more to consume more energy. In effect, the work by Z. Fan is attempting to move the burden of load leveling and shaping away from the utility and towards the energy consumer. A corollary exists between the WTP parameter proposed by Z. Fan and the PMCS outlined in this work. Instead of the EV owner providing a WTP parameter and allowing the charging process to proceed until electric costs reach the WTP value, the PMCS strives to lower the cost of electricity at all times so that a WTP parameter is not required. In effect, the PMCS attempts to keep its operating point near the origin of the plot show in Figure 14.

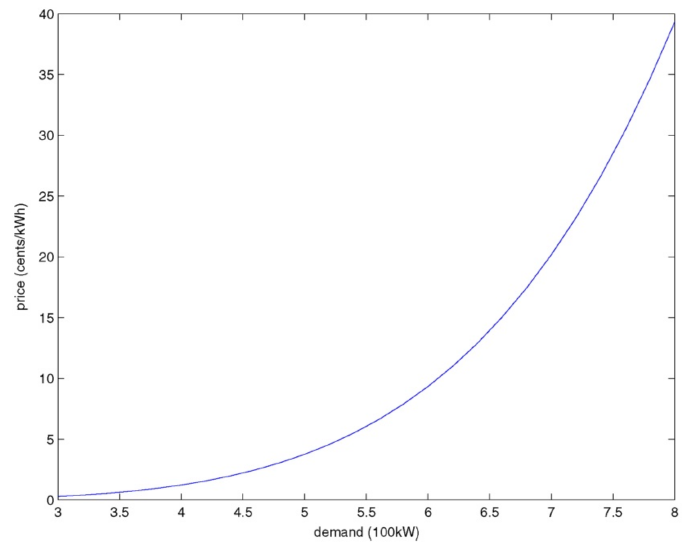



FIGURE 14: Variable pricing structure utilized by Z. Fan, et al [28].

Other research has used dynamic pricing signals as a direct input into a control system. This input signal is utilized in optimization routines to minimize cost and maximize charge activity. By taking the human factor out of the control system, the power grid benefits from reduced peak demand and the electricity consumer benefits from cheaper energy costs. In works by M. Rastegar, et al. [25] and P. Sanchez-Martin, et al. [27], the variable pricing signals are utilized in this manner. In both cases, primary cost savings are obtained from shifting charging activity from peak to valley price periods. This is similar to time-of-day shifting but the control and optimization algorithms rely on cost rather than time since they may not always be related.

In works by P. Finn, et al. [26] and N. Rotering, et al. [22], dynamic pricing signals are used in forecasting algorithms to provide spot market or day ahead pricing for electricity consumption. These works are beneficial in that future charging can be dispatched accordingly to the forecast provided. P. Finn utilizes an optimization algorithm similar to Rastegar and Sanchez-Martin. The results of this study can be seen in Figure 15.

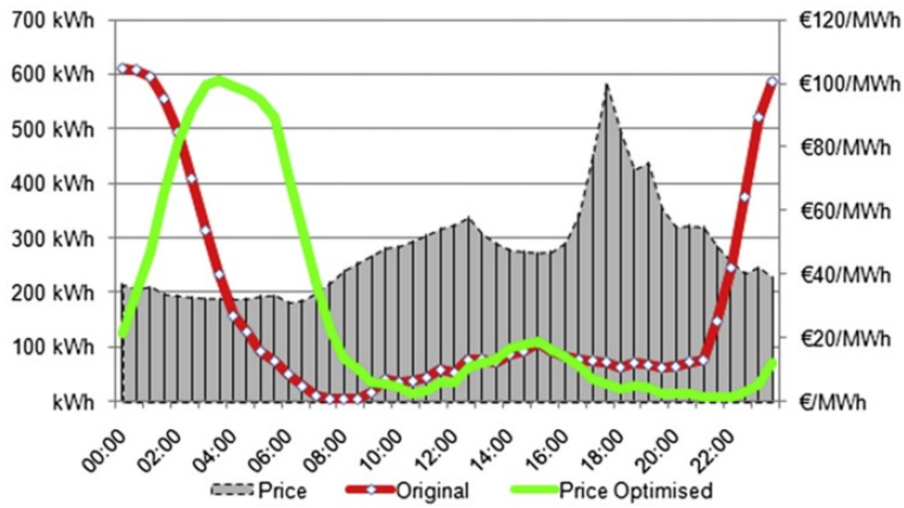



FIGURE 15: EV load profile pre and post price optimization [26].

Some research has used simple dynamic pricing signals to try to alter EV owner behavior for charging directly to achieve beneficial load shaping [24]. In these scenarios, the EV owner is prompted with a given cost prior to beginning a charge. It is then up to the customer to decide if it is economically worthwhile to charge at that time. Again, this scenario is useful for residential charging, but not for commercial charging locations where overall demand is important. By simply displaying the instantaneous cost at the start of the charge, fluctuations in price can create large costs in the middle of a charge cycle, especially if the charging activity takes place during the workday which coincides with peak demand periods. Also, there is no benefit to the demand level as some EV owners may choose to charge at any time.

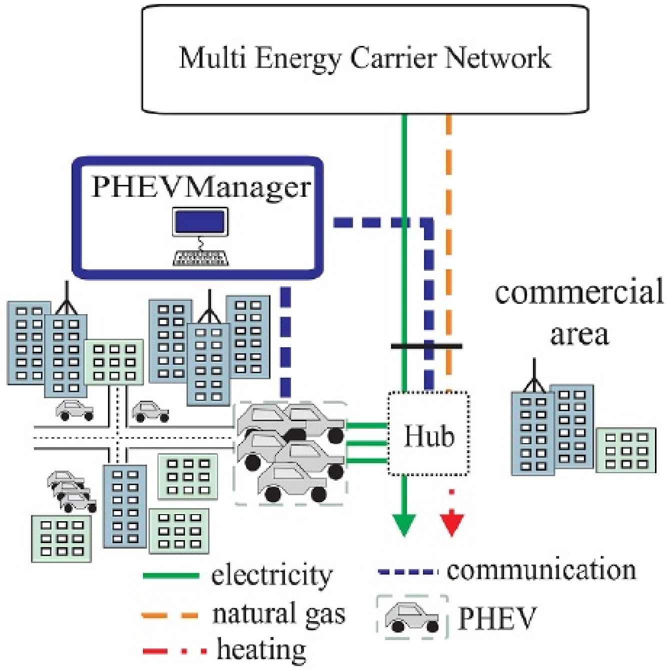



FIGURE 16: Communication infrastructure required between utility and EV owner [21].

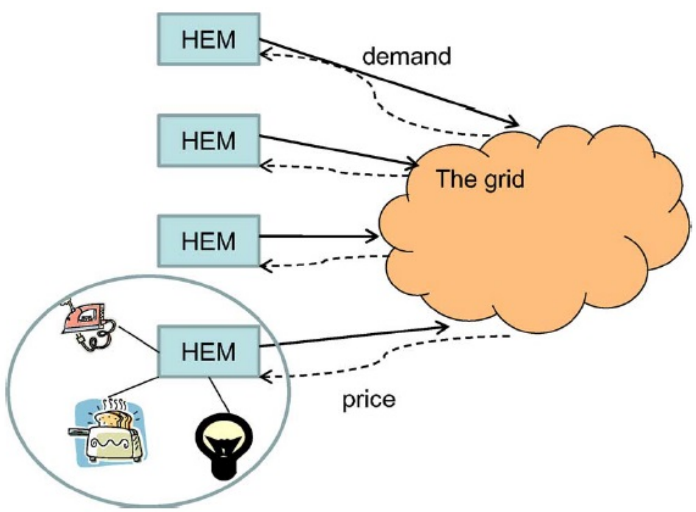



FIGURE 17: Home Energy Managers (HEM) utilized in residential cases to receive pricing information [28].

The results of variable pricing based control methods are very promising; however, there are still some disadvantages to such a strategy. One primary disadvantage is the cost required to implement real-time pricing signals from the utility to the consumer. Implementation would require mass installations of Advanced Metering Infrastructure (AMI) and large communications networks. This cost is not feasible when compared to the cost savings to the utility and consumer. Figures 16 & 17 show the type of infrastructure required. Figure 16 pertains more to a commercial charging location in a city. Since charging stations are typically distributed over a wide geographical area and do not tend to concentrate in one location within a city, it is easy to see how the cost of implementing this infrastructure could grow exponentially. On the other hand, Figure 17 shows the infrastructure required in a residential scenario. The Home Energy Manager (HEM) is used to send demand signals to the utility and receive dynamic pricing signals to base control decisions on. One example of this type of technology is General Electric's Nucleus. Nucleus gathers energy use information from appliances and meters located throughout the home and provides the information needed to help reduce energy consumption or encourage the consumer to change their behaviors [29].

## Ancillary Services

In addition to control algorithms and strategies to reduce demand and costs related with PHEV charging, there are control strategies that have been developed to provide ancillary services to the grid. A summary of prior art discovered relating to EV charge control for providing ancillary services is listed in Table 4. These include

TABLE 4: Summary of prior art utilizing control for ancillary services.

| Date | Primary Author | Charge Control Method | Title |
|---|---|---|---|
| Sep-09 | T. Markel | Renewable Integration | Communication and Control of Electric Drive Vehicles Supporting Renewables [33] |
| Apr-10 | K. Mets | Residential Direct Load Control | Optimizing Smart Energy Control Strategies for Plug-in Hybrid Electric Vehicle Charging [30] |
| Sep-10 | R.J. Rei | Grid Frequency / Voltage Control | Grid Interactive Charging Control for Plug-in Electric Vehicles [32] |
| Sep-11 | A. Nebel | Direct Load Control | Vehicle to Grid and Demand Side Management - An Assessment of Different Strategies for the Integration of Electric Vehicles [31] |

demand profile smoothing or balancing [30], [31], [20], frequency and voltage control of the grid [32], and integration of renewable energy sources [33]. These control strategies focus only on the behavior of the utility grid and any cost benefits or drawbacks are secondary. Grid frequency and voltage levels are highly dependent on the relation between generation capacity and energy demand. Excess generation or low demand levels can cause both frequency and voltage levels to increase. Conversely, high demand or low generation capacity create voltage sags and low frequency situations [34]. Figure 18 represents this relationship.

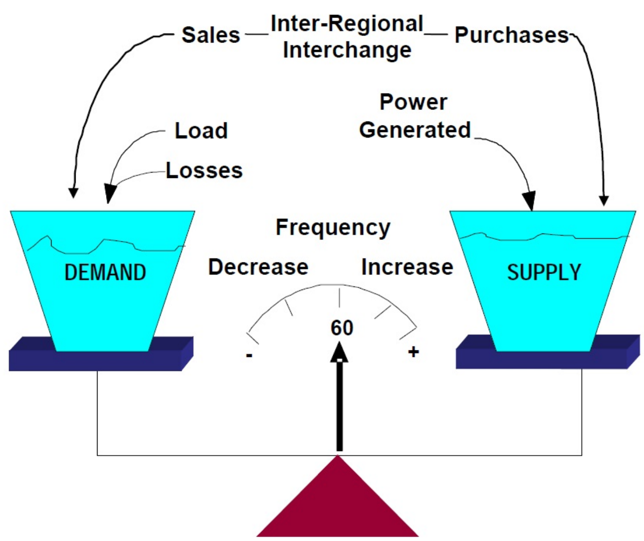



FIGURE 18: Relationship between supply, demand, and grid frequency [34].

Due to the size of PHEV charging loads, these loads can be dispatched to help with the control process of managing frequency and voltage levels. By limiting or increasing PHEV energy demand, frequency and voltage levels in specific grid regions can be more accurately controlled [32]. Figure 19 represents the simulation results from a demonstration where a single PHEV battery load was used to control voltage and frequency on a subsection of a power grid. There was a high level of control demonstrated; however this control method may not be preferable due to driving patterns of some PHEVs.

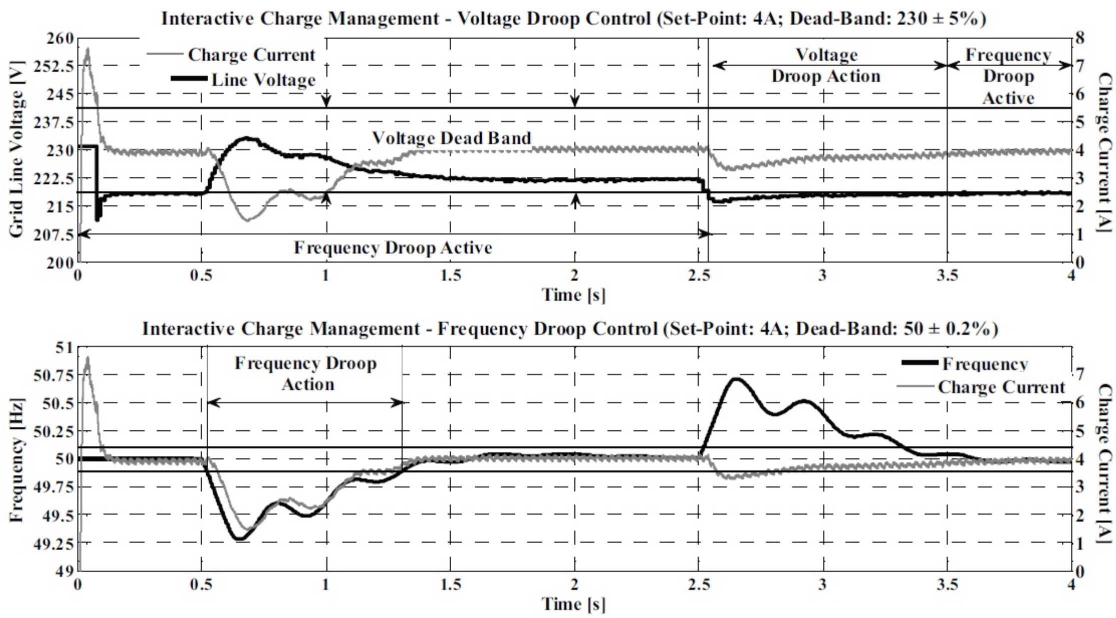



FIGURE 19: Simulation results showing frequency and voltage regulation by controlling PHEV charging [32].

Since renewable sources of electricity are often intermittent and depend on weather patterns, PHEV loads can be utilized to better utilize the renewable generation capacity [33]. The battery storage provided by PHEVs is a large capital investment and since PHEVs are parked the majority of the time, it is beneficial for the grid to use these as energy storage for renewable sources. Control strategies such as these for PHEV charging only benefit the utility and are not beneficial for commercial PHEV charging systems. In addition, current plug-in hybrid electric vehicles do not support this technology.

Other sources note that by incorporating Direct Load Control (DLC) at the EV charging level, the residual electrical demand profile can be smoothed or leveled. In Figure 20, A. Nebel shows that EV charging and discharging activity can be incorporated into the utility grid to help smooth the demand profile [31]. Again, this control strategy assumes that technologies enabling vehicle to grid and energy storage are available in plug-in hybrid electric vehicles. Similarly in Figure 21, K. Mets shows the smoothing effect that controlling EV charging can have for a case where there is 30% EV penetration.

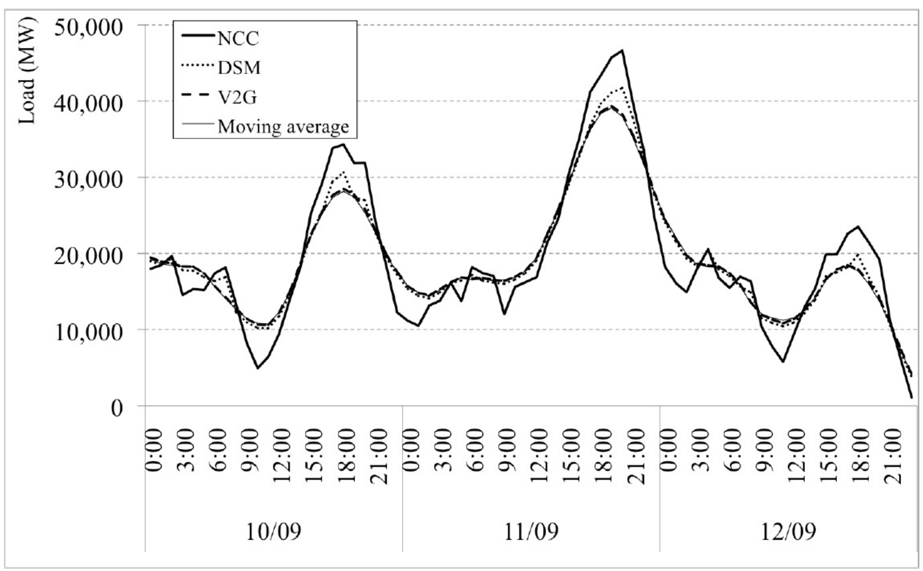



FIGURE 20: Simulation results showing demand profile smoothing by controlling PHEV charging and utilizing vehicle to grid capability [31].

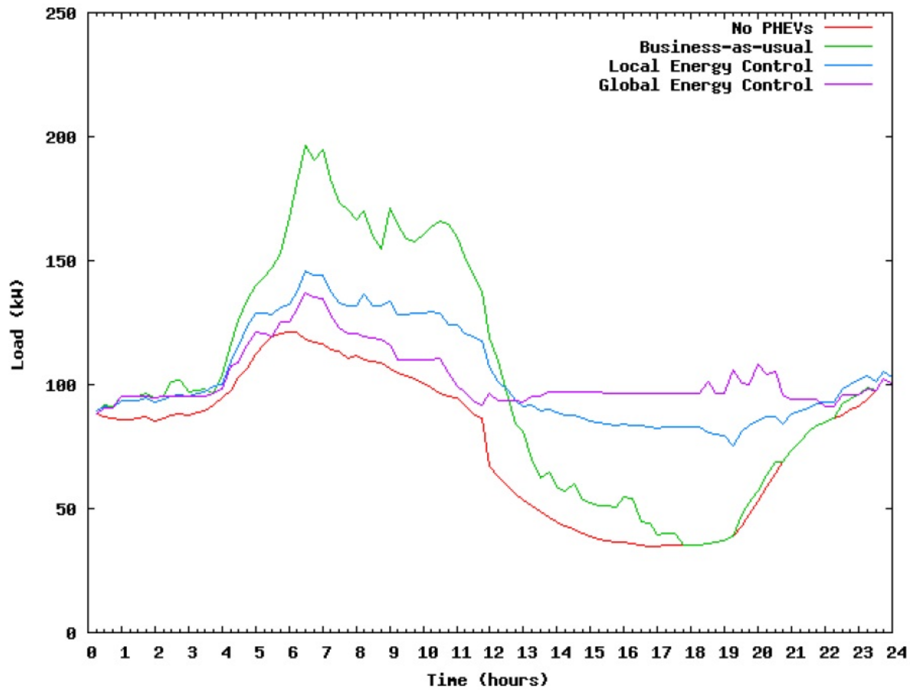



FIGURE 21: Demand profile smoothing for 30% EV penetration [30].

In summary, there are many control strategies introduced in the literature reviewed here. The majority of control scenarios focus on simple time of day charge scheduling or more advanced real time pricing strategies. Others focus on ancillary services such as load leveling or smoothing, frequency and voltage control, or renewable energy source integration. Each strategy has its own benefits and disadvantages. The work in this dissertation looks to combine the benefits of several of the works listed here to provide demand side management of EV charging activity for Commercial & Industrial electric ratepayers.

## Demand Forecasting Algorithms

The PMCS described and designed within this work relies heavily on the forecasting of electricity demand profiles for scheduling PHEV charging activity. Therefore, a literature review was also performed on various forecasting algorithms currently utilized for forecasting electrical demand. Utilities use such algorithms for dispatching generation capacity due to the time it takes for some generation sources to come on-line. Bulk generation of electricity typically utilizes coal fired or nuclear steam turbines which produce cheaper electricity but take longer to start up and shut down. Peaking plants are utilized by electric utilities to account for transient fluctuations in electrical demand. Peaking plants are typically natural gas fired and can be started or shut down much quicker but do cost more to operate. Since the cost of electricity varies with generation mix and demand, accurate forecasts are extremely important due to the size of PHEV charging loads and the potential impact they can have during peak demand periods. Demand forecasting is a fairly mature field in that there are several companies and utilities that use or sell this information to dispatch generation capabilities.

Most demand forecasting algorithms fall into one of two categories: statistical methods and artificial intelligence based methods. Both categories could be used for predicting demand levels and profiles as required by this research. Statistical methods forecast current or peak loads by using previous load values in combination with a variety of exogenous variables such as weather, holidays, or other variables. Examples include similar-day, regression and time series methods. Artificial Intelligence

(AI) based forecasting techniques classify input data and associate it with respective forecasts and do not make use of the specific relations utilized in statistical methods. Examples of AI forecasting methods include neural networks and fuzzy logic. This study will examine the results of both statistical and artificial intelligence forecasting techniques.

Traditional statistical models such as auto regressive, moving average, auto regressive moving average, auto regressive integrated moving average, linear regression and regression tree analysis have been proven to result in accurate forecasts. However there are a number of newer statistical models that have been developed and refined over the past few decades. These include adaptive grey-based approaches [35], and exponential smoothing approaches [36]. Mean Absolute Percent Error (MAPE) values of between 0.5% and 8% can be achieved depending on the forecasting algorithm chosen. In [36] Taylor demonstrated that exponential smoothing algorithms can achieve excellent MAPE values of less that 1% for short term demand forecasts which can be seen in Figure 22.

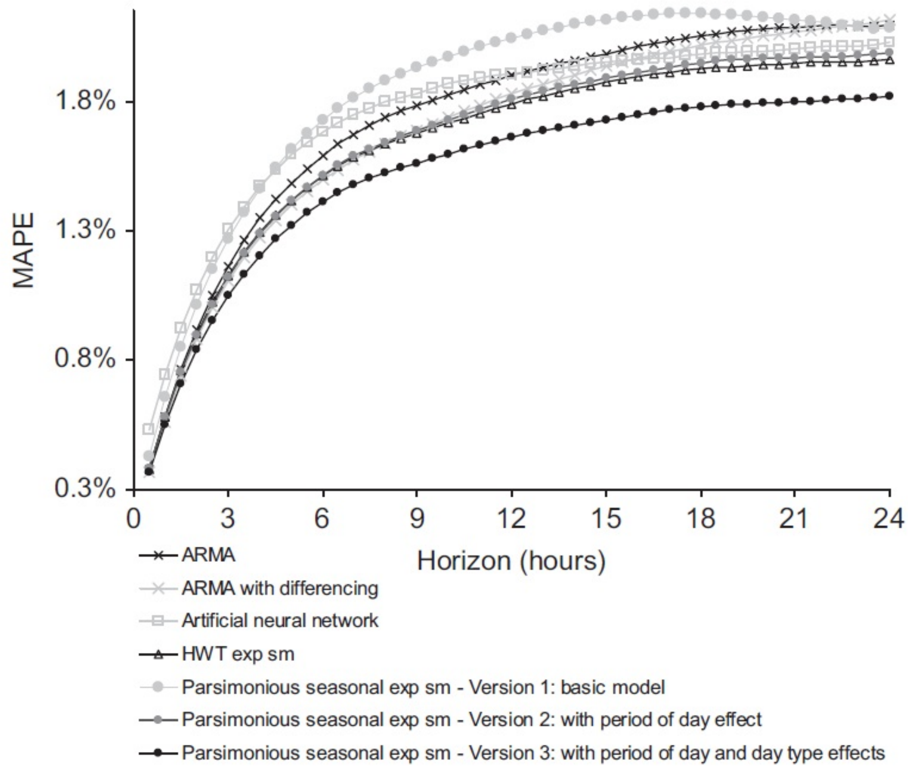



FIGURE 22: MAPE of various forecasting algorithms simulated [36].

Artificial Neural Networks (ANNs) are another popular method of forecasting linear time series such as energy demand profiles [37], [38], [39]. ANNs produce excellent results with minimal MAPE and can use a number of various input quantities. Due to strong correlations between temperature, dew point and electric demand, ANNs commonly use easily measurable quantities such as temperature to predict demand. Neural network prediction models can achieve great MAPE values in the range of 0.5% to 1%. However, a big disadvantage of ANNs is the need for large databases of training data for developing the network. Additionally, the time required for training neural networks can become significantly long in order to achieve lower MAPE.

Linear time series forecasting algorithms are of great importance in this study. There are numerous works in scholarly journals detailing specific forecasting algorithms, and the few listed in this review are only representative of the many available. Several algorithms will be studied to determine the best algorithm to use in this work.

### 2. Studies Indirectly Related

In addition to the works regarding PHEV charge control and demand forecasting algorithms, there are other studies that are of great importance to this research. Demand response programs have been developed and used throughout the United States recently to control peak demand and prevent the need for new generation facilities. This section will detail demand side management programs and will highlight their importance as related to this research. The PHEV control system designed and developed through this research should provide capability for integration with demand response programs from the local utility.

Demand Side Management (DSM) or Demand Response (DR) is the process of promoting energy consumers to use less energy during peak demand periods through education programs and financial incentives. Overall reduction of energy consumption is possible but is not usually the case for DSM programs. Instead, DSM and DR programs often promote consumers to shift demand to off-peak periods. DSM and DR programs have numerous benefits to both the energy consumer and the utility. Various forms of DR are detailed in Figure 23(a) while Figure 23(b) details the numerous benefits of incorporating such programs.

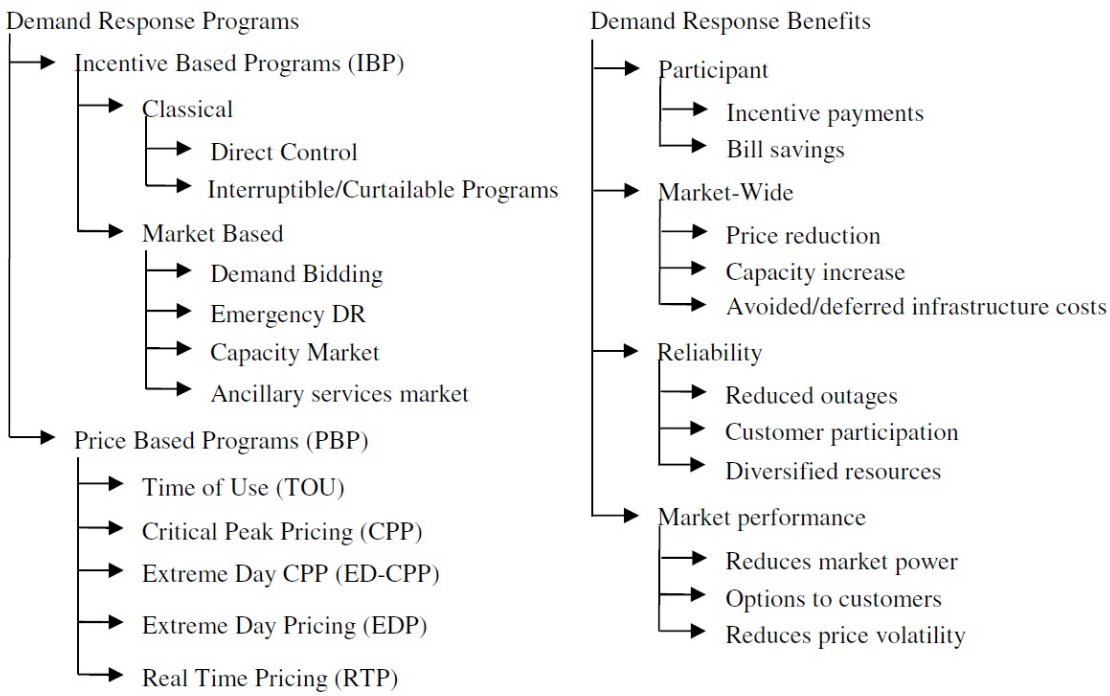



FIGURE 23: (a) Various types of demand response programs. (b) Benefits of DR programs [40].

Through research by the Central Research Institute of Electric Power Industry in Japan [41], the market potential of DR programs is studied. This study uses a DR program developed by Tokyo Electric Power Company that controls lighting and air conditioning loads for selected office buildings during peak demand periods. The DR program did produce favorable results by limiting commercial electric consumption by 4.7%. However, through surveys with the electric consumers included in the DR program, workers comfort and their subjective working efficiency were affected. This study proves that DR programs must be properly designed, so that peak demand savings for the utility remain beneficial without creating significant negative effects for the DR participants.

The primary benefit from most DR programs is derived from the peak clipping of demand profiles provided during peak demand periods. Other benefits include economic benefits to the utility and the electric consumer, and reliability / stability of the utility grid [42]. A DR program enacted by Louisville Gas and Electric Company (LG&E) [52] has proven all of these benefits. This program uses direct load control switches installed on air conditioning systems, pool pumps, and water heaters to manage demand during summer months. With approximately 25% of all LG&E customers participating in this program, peak savings of 169MW were obtained in July 2011. In addition to the demand benefits provided, economic and environmental benefits are also realized through the prevention of constructing new generation assets that otherwise would be required.

DR programs are extremely beneficial for the electric utility. An ideal PHEV charging control system will integrate DR capability to prevent negative effects from EV charging activity. Numerous scholarly studies are available concerning the success of DR programs; however the consensus between the studies is that DR programs are extremely beneficial and cost effective as long as they are properly managed.

## G. Justification of Novelty

The potential for peak electrical demand issues arises for electric utilities due to the growing market for PHEVs. Compounding the issue is the fact that the majority of PHEVs in the vehicle market today have limited all-electric range which often requires charging during the day at places other than at home. Charging demand not only affects utilities due to the extra generation required during peak demand periods, but it also affects the electric ratepayer with increased electric costs that vary with time-of-use. Demand response programs aim to limit electricity demand during peak demand windows therefore preventing those negative effects.

The majority of demand response programs are aimed at residential demand. However with commercial billing structures that include peak demand charges or time-of-day electric rates, demand response programs can be of great benefit to commercial electric consumers as well. Additionally, demand response programs are commonly controlled by the utility and require additional communication infrastructure between the customer and the utility. The PHEV charge control system developed here provides the benefits of demand response to both the utility and the electric consumer without the need of additional communication infrastructure. An autonomous control system can make intelligent decisions regarding when to charge PHEVs by predicting when demand peaks will occur.

As PHEVs become more popular due to the potential for greenhouse gas emission reductions and fuel savings, scholarly articles have proposed several control algorithms for limiting the negative impacts that increased electricity demand could induce. These control schemes primarily focus on time-of-day charge control where PHEV loads are simply shifted to off-peak periods or on variable energy pricing in de-regulated energy markets that are used to optimize charge times. Time-of-day charging is simple; however it creates problems for EV owners that require charging during the day due to limited electric range. Dynamic pricing schemes require additional communication infrastructure and capital costs of implementation usually outweigh the potential savings. Another issue with dynamic pricing is that pricing structures are normally determined in a day-ahead fashion. Therefore, the potential exists for pricing not to match generation capacity and demand. No control algorithms discussed in the literature reviewed considered directly monitoring electricity demand and controlling charging based on short term demand forecasts as proposed by the work included here. This has the potential to provide the best benefits for both the utility and the electric consumer.

The number of PHEVs allowed to charge at any instant can be determined with accurate demand forecasts so that charging activity will not drive peak demand higher or create new peaks. Additionally, by adding communication between the control system and the vehicle, state of charge can be utilized as a determining factor when some charging must be halted or prioritized. Battery system health can be optimized by intelligently scheduling charging based on departure times and battery state of charge. Local (end user) demand management systems can provide accurate control of PHEV charging while still providing benefits to both the utility and the electric consumer. Local demand management will not require large financial investments in communication infrastructure or remotely managed direct load control switches.

# CHAPTER II
# BACKGROUND INFORMATION

The popularity of alternative fueled vehicles will rise as prices continue to increase for petroleum based gasoline. Electric Vehicles (EVs) such as the Nissan Leaf [13] or Plug-In Hybrid Vehicles (PHEVs) such as the Chevrolet Volt [12] have become an acceptable alternative to traditional Internal Combustion Engine (ICE) based vehicles. The popularity of these electric drivetrain vehicles can be attributed to the significant cost savings in fuel over traditional ICE powered vehicles. Instead of obtaining energy from the combustion of gasoline, EVs and PHEVs obtain their motive force from chemical energy stored in a battery. The energy required by these battery systems during the re-charging process is commonly obtained from the utility power grid therefore creating a new list of potential issues. The extra electrical demand due to EV charging adds to an already overloaded grid. However, added load is not necessarily detrimental to the growing adoption rate of PHEVs. This additional electrical demand can be detrimental if this load coincides with peaks in the demand profile which may or may not be the case depending on where and when the charging activity takes place. Additionally, significant electric cost increases can be incurred due to the rate structure commonly followed by commercial entities such as schools, shopping centers, and businesses that provide daytime EV charging capabilities. This section will provide valuable background information regarding the types of EV charging infrastructure, electrical demand and energy consumption, typical demand response programs, and electric billing structures that may be affected by EV charging activity.

## A. Electric Vehicle Charging Infrastructure

Charging infrastructure was developed alongside the development of PHEVs to create a user friendly and safe method of re-charging vehicles. Charging stations, or Electric Vehicle Service Equipment (EVSE) as they are commonly called, come in numerous types and can be obtained relatively easy. Figure 24 shows a few of the various types of EVSE that are available today.

FIGURE 24: Representation of various charging stations available today [43].

Charging stations can be classified into one of three major types. Level I chargers are the most common and also the most inexpensive. These commonly run off of single phase 120 VAC supply and charge at rates of 1.2kW to 2kW which will provide a full charge to a depleted vehicle in 10-20 hours, dependent on the size of the vehicle's battery. Level I capable vehicles do not always require dedicated

EVSE, some charge through a NEMA 5-15R outlet and can do so using a standard electrical extension cord. Level 1 EVSE are typically portable and used in the case of an emergency when faster charging capability is not available. Level II and III capable vehicles require dedicated EVSE per the national electric code for safety. Some manufacturers offer level II charging stations for residential use [44], however most level II stations are found at public charging locations. Many locations such as malls, public parking garages, and shopping centers install level II stations for customer use [45]. Level II stations are typically supplied by 208-240 VAC and obtain charge rates of 2kW to 15kW. A depleted EV can be charged in approximately 4 to 8 hours depending on battery size. Level II EVSE units and some Level I units use the SAE j1772 connector standard instead of the NEMA 5-15R connector for safety [46]. In both Level I and Level II EVSE, the AC voltage is passed directly to the vehicle's on-board battery charger which then converts the voltage to DC. Level III charging stations are much less common and are still under development. These EVSE use greater amounts of power and current to bypass the vehicles on-board charger with a fast and reliable DC charge in minutes instead of hours. Level III DC charging is ideal for public charging infrastructure. Typical applications include charging large vehicles with big batteries such as buses and commercial or service fleets with very little recharging downtime. Level III chargers commonly provide 400 to 600 VDC charging levels and use a different connector standard than level I and II chargers [47]. Figure 25 shows the relationship between EV charger levels/types, typical locations, charge times and relative cost. Additionally, Table 5 provides a summary of charging station types.

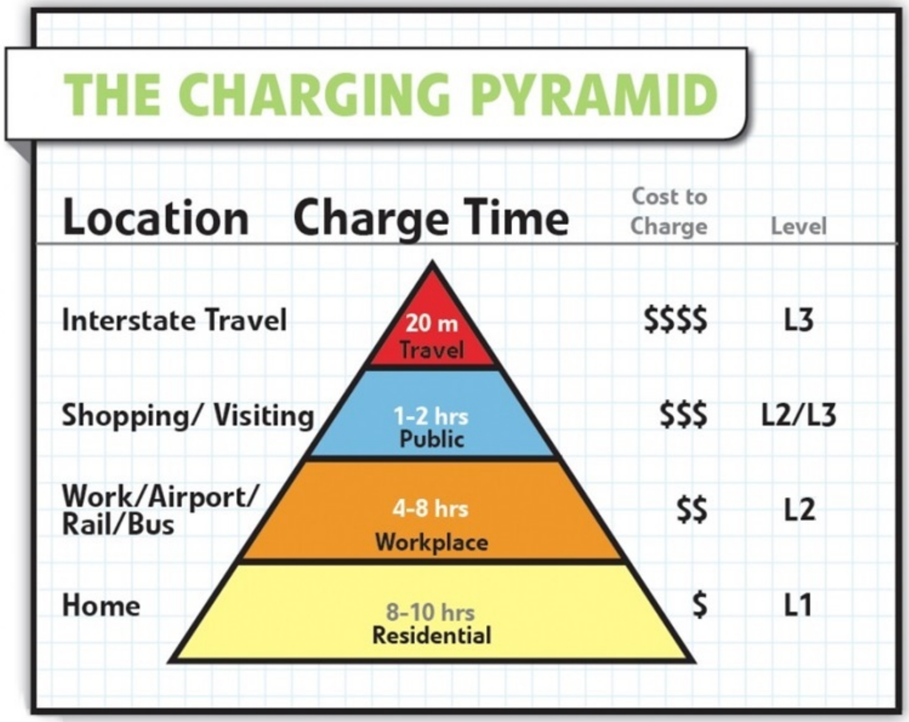



FIGURE 25: Charging pyramid showing relationship of EV charger levels.

As shown in Table 5, there are three basic types of charging stations. A problem arises with charging infrastructure in that there are few standards set in place to regulate the design and operation of these critical pieces of equipment. Individual manufacturers often offer proprietary control systems and software for monitoring usage, but due to the lack of standards none of these systems communicate with each other or the smart grid as a whole. This creates difficulty in developing a control system that can be implemented to monitor and regulate charging activity.

TABLE 5

Summary of EVSE charging levels [47].

| **Charging Level** | **Power Delivered (kW)** | **Connector Standard** | **Information** |
|---|---|---|---|
| 1 (I) | 1.2 to 2.0 | NEMA 5-15R or SAE j1772 | Requires 10 to 20 hours to charge vehicle depending on vehicle and battery type. No special electric infrastructure required. |
| 2 (II) | 2.8 to 15 | SAE j1772 | Charges vehicle in 4 to 8 hours based on battery type and capacity. Requires special EVSE to provide isolation, protection and safety. |
| 3 (III) | >15 | CHAdeMO & others under development | Provides up to 80% charge in 30 minutes. Requires 3 phase 480 VAC service and charges at DC voltages rather than AC. |

## B. Electricity Demand and Energy Consumption

In order to understand the effects that EVSE have on the utility grid, it is first necessary to understand the basics of electricity demand. For simplicity, this description will assume that the voltages and currents measured are balanced between 3 phases. Power can be classified into one of three types: real or true power (P) measured in Watts, reactive power (Q) measured in VARs and complex or apparent power (S) measured in VA. The impedance phase angle ($\theta_p$) between the voltage and current waveforms determines the magnitude of the three types of power. Capacitive loads are represented by negative impedance phase angles and negative reactive power; whereas inductive loads are represented with positive phase angles and positive reactive power values. Figure 26 represents the relation between the three measures of power through the power triangle.

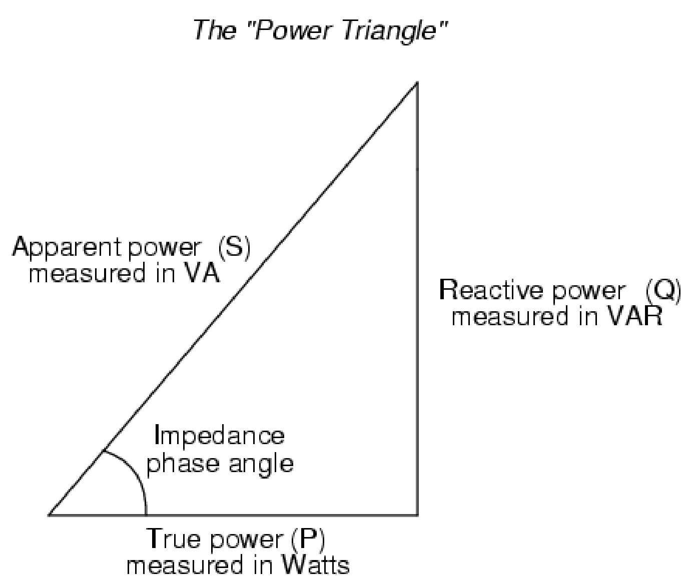



FIGURE 26: The power triangle relates true, apparent, and reactive power [48].

$$P = 3|V_p||I_p|\cos(\theta_p) \tag{1}$$

Power factor is a common measurement used to determine the value of the total impedance angle for a given load. The power factor is a value between 0 and 1 and is calculated by evaluating the cosine of the impedance phase angle. Power factors approaching or equivalent to 1 are preferred, representing equivalent apparent power and true power. Apparent and reactive power can be easily determined from true power through simple trigonometric functions. True power is commonly measured for balanced three phase systems using Equation (1).

In power systems, there are two common measurements used to determine how much energy is consumed. Energy consumption is commonly measured in kilowatt-hours (kWh) and represents total energy consumed over a given time period. Similarly, energy demand is commonly measured in kW (real power) or kVA (apparent power) and represents the instantaneous energy consumed at any 1 point in time. For example, a 1kW electric motor with a power factor of 0.85 consumes 1kW or 1.176 kVA of instantaneous demand. If this motor runs for 2 hours, the total energy consumption is equivalent to 2 kWh (1 kW * 2 hours = 2 kWh) [49].

Electricity demand varies throughout the day for most utility loads. This variance is primarily due to heating or cooling energy consumption and lifestyles of electricity consumers. The variance of electricity demand poses a serious problem for utilities since generation capacity must closely follow demand levels to prevent detrimental variations in voltage levels and frequency on the grid. Ideally utilities would prefer system loads to be flat with minor changes, however since it is not, utilities must dispatch reserve generation capacity to account for the difference. These peaking generation facilities can be online within a few minutes where the base load generation takes hours to shut down and start up. High demand peaks and low demand valleys determine the size of peaking plants required. Figure 27 represents the daily demand for the University of Louisville Belknap Campus. The demand profile shown is for a typical Sunday and Monday in August where average demand is higher due to cooling loads. Energy consumption (in kWh) could be calculated by integrating the area beneath the demand curve in Figure 27 while also taking the power factor into account.

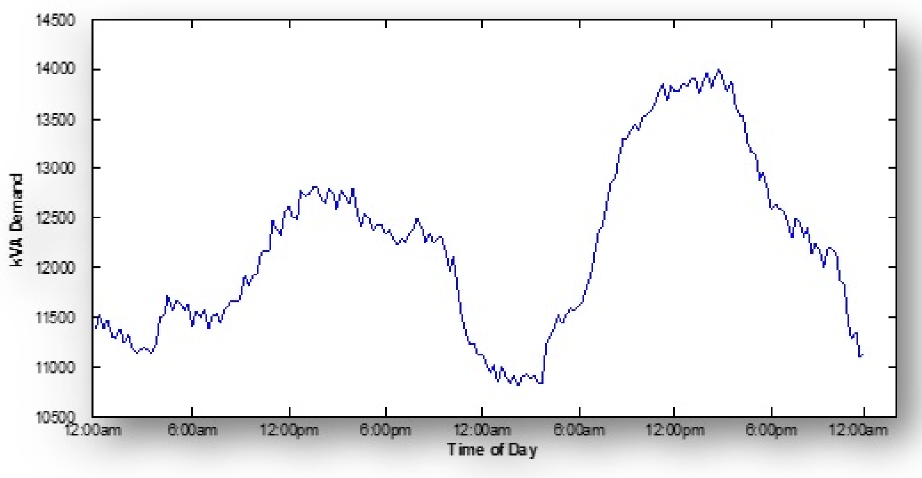



FIGURE 27: University of Louisville Belknap Campus kVA demand measured in August 2010 by Louisville Gas & Electric [50].

## C. Demand Response

Understanding electric demand is important when related to PHEVs because of the size of the added load of charging activity. PHEV charging activity during the day (late morning to early afternoon) directly coincides with the demand peaks of existing loads as shown in Figure 27. This increase in load results in generation capacity problems for utilities that must be overcome to keep the grid operating at nominal voltages and frequencies. Due to the inelasticity of electricity demand, electric consumers will not willingly change usage patterns based on supply and demand only. If financial incentives are provided for less energy usage, consumers are more likely to change electricity usage habits.

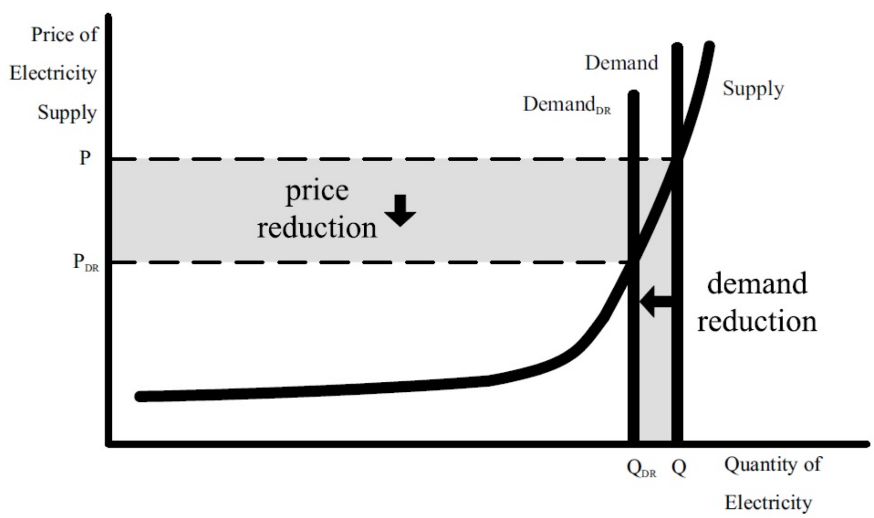



FIGURE 28: Exponential behavior of electricity prices [51].

As electricity demand increases, large increases in cost result. Figure 28 shows that a slight reduction in electrical demand can result in significant cost savings by the consumer [51]. Demand response is a method of reducing energy demand by providing financial incentives to the consumer with the purpose of promoting less energy consumption. Demand response programs are commonly implemented by utilities when wholesale market prices are high for electricity or during times when high demand levels jeopardize electric system reliability [40]. There are numerous benefits to demand response programs with the most important benefit being improved resource efficiency of electricity generation. Other benefits include: financial benefits for the program participant (or electricity consumer), market-wide financial benefits such as lower wholesale market prices, and reliability benefits such as outage reductions and increased operational security of the utility grid [51].

Implementation of demand response programs in the United States is limited due to capital costs associated with the installation and management of such systems. Despite the costs, Louisville Gas and Electric (LG&E) Company has implemented a demand response program in Louisville, Kentucky. This program provides demand response through direct-load control switches installed on air conditioners, water heaters and swimming pool pumps. These switches can be remotely operated by the utility during peak demand periods to reduce peak demand. Approximately 25% of LG&E customers currently participate in this program resulting in peak reductions of up to 169MW. By participating, customers receive fixed bill credits during the months of June to September when demand is the highest [52].

The control system described in this dissertation provides demand response capabilities by limiting increased demand due to PHEV charging activity. This is achieved by intelligently scheduling charging activity so that this activity does not correspond with peak demand periods. Instead of direct financial incentives such as bill credits or reduced electric rates, this control system will reduce peak demand charges incurred by the owner of the EVSE. Forward-thinking college campuses, shopping centers, malls, and other commercial electricity consumers with multiple charging stations could achieve great financial benefits from such a system.

## D. Electric Rates and Billing Structures

Due to differing amounts of electric power consumed, billing structures commonly differ between residential or basic electric service consumers and commercial or industrial consumers. Since commercial and industrial consumers utilize approximately 61% of the energy produced according to Figure 29, utilities commonly bill for both energy usage and electric demand.

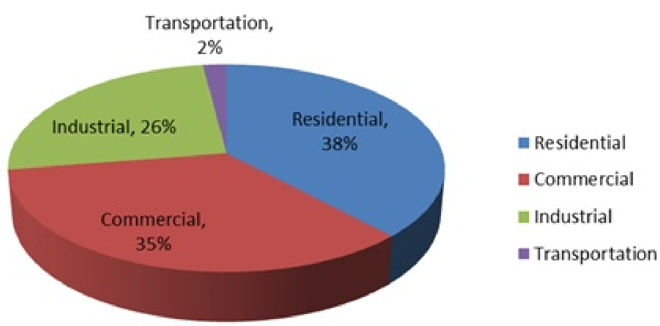



FIGURE 29: Electricity usage by major consuming sectors (2010) [53].

In view of the rapidly growing market for EVs, some municipalities and electric utilities in the US have developed distinct billing structures for EV infrastructure and associated electrical demand [54], [55]. However some state, city, or local regulatory commissions do not allow these special rate structures. This raises concern because the charging infrastructure location, i.e. business or residential, factors heavily into the electrical cost per unit of energy consumed due to excessive differences in electrical rate structures when compared to traditional EV charging models.

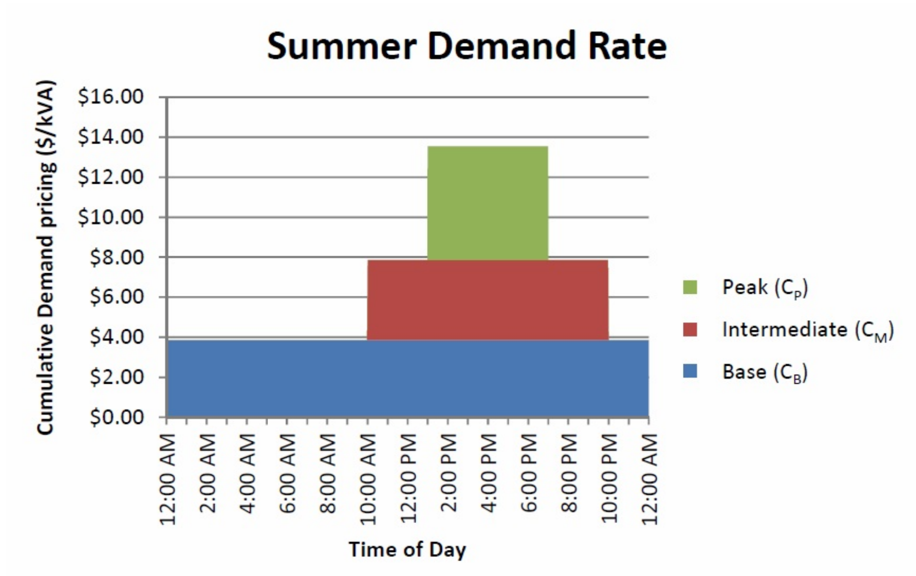



FIGURE 30: Typical summer demand rate structure and windows [1].

In the US, residential electricity ratepayers commonly pay for electricity based on energy consumption only through an energy charge per kilowatt-hour of energy consumed ($/kWh). This rate normally is fixed and does not vary throughout the day. For example, in regions of the United States where coal is the primary source of electrical generation such as Kentucky, these residential rates average around $0.07 to $0.10 per kWh consumed [1]. On the other hand, the emergence of smart grid technologies have stimulated the development of adaptive rate structures [56], [57].

In contrast, Commercial and Industrial (C&I) electric ratepayers, or other large electric consumers which constitute the majority of businesses, shopping centers, academic campuses and manufacturing facilities, generally pay for electricity consumption based not only on total energy consumed, but also on peak electric demand measurements. C&I rate structures typically consist of an energy charge component that is similar to the residential charge, but much lower. For example, in Kentucky, C&I rates for energy consumption range between \$0.03 and \$0.04 per kWh. However the additional demand charge which is based on the peak electrical demand measured for given intervals throughout the day is quite significant. In Kentucky, these demand rates for C&I electric ratepayers range between \$11.00 and \$14.00 per kVA of instantaneous demand [1]. Typically the total monthly demand charge and total energy charge each account for approximately 50% of the total electricity bill for large energy consumers. Equations (2) & (3) represent the monthly electric rate structures for residential and C&I ratepayers, respectively, in Kentucky. Constants $C_0$ and $C_1$ represent energy cost coefficients and $C_P$, $C_M$, and $C_B$ represent demand cost coefficients for peak, intermediate, and base periods as illustrated in Figure 30 [4]. Further, $C_P$ is typically higher than $C_M$ and much higher than $C_B$. For example, in parts of Kentucky these rates are $C_P$=\$5.70, $C_M$=\$4.00, and $C_B$=\$3.85 [1]. $x_t$ and $y_t$ represent total energy consumption (in kWh) and total electrical demand (in kW or kVA), respectively.

$$Residential\_Cost = C_0 \sum_{t=1}^{31} x_t \tag{2}$$

$$\begin{aligned} C\&I\_Cost = C_1 \sum_{t=1}^{31} x_t + C_P * \max_{1 \le t \le 31} \{y_t^{Peak}\} \\ + C_M * \max_{1 \le t \le 31} \{y_t^{Mid}\} + C_B * \max_{1 \le t \le 31} \{y_t^{Base}\} \end{aligned} \tag{3}$$

In addition, due to the high electric consumption rates of C&I electric ratepayers, there is typically a clause in the billing structure that imposes a minimum demand charge based on a percentage of the highest electric demand for the previous 11 months. This billing clause is included in most billing structures to prohibit or discourage customers that have high energy consumption for a short period of time during the year, and low energy consumption the rest of the time. An example of this type of electric consumer could be a football stadium that only consumes electricity during the football season but is dormant the rest of the year. In the case where the minimum charge is encountered, the availability of EV chargers would be higher than forecasted since additional load would not drive the demand cost for the electric ratepayer. In order to account for this, the power monitoring and control system outlined in this dissertation assumes a worst-case scenario where this minimum is never hit.

Billing structures for commercial and industrial time of day ratepayers create a disincentive towards the use of electricity during peak demand periods by increasing the total cost (energy + demand) of electricity during those periods. Most electric loads, such as heating and cooling or lighting loads, are inelastic and will not change due to the increased cost. However, commodity loads that may not be necessary can be changed or re-scheduled so that they do not coincide with peak demand windows.

PHEV charging may not be considered a commodity load since electric vehicles require electric charge in order for the driver to safely make it to their destination. On the other hand, with newer and faster charging technologies such as level II or III EVSE, charge times are greatly reduced for PHEVs. These charge cycles can be postponed or re-scheduled so that the resultant load is not coincident with the peak demand for the day.

# CHAPTER III
# RESEARCH METHODS

The current charging station model accepted today for residential electricity consumers is not scalable for commercial time of day electricity ratepayers that pay a peak demand fee as part of their electricity costs. The increase in electric costs due to electric vehicle charging activity in C&I environments results in a significant disincentive to EV adoption for these facilities. Additionally, the potential peak demand introduced by PHEV charging can create significant issues affecting grid stability including lack of generation capacity and frequency or voltage deviations. A solution is required that provides demand response for EV charging to reduce peak demand charges. This solution must take into account that charging activity is inelastic and most EV owners are unwilling to change charging activity.

A modular PHEV charge control system will be developed to provide demand management of PHEV charging loads and that will decrease costs incurred by the commercial electric ratepayer. This system will be implemented at the charging station location to prevent expensive communications infrastructure between the EVSE and the utility.

Several linear time series forecasting algorithms will be studied to determine the optimum for predicting the demand profile of the end user. The selected forecasting algorithm will be implemented into the control strategy and will be analyzed based on performance and peak demand savings. The analysis of cost savings will be utilized to determine the feasibility and payback of implementing such a control system.

Educating the EV owner about performance of the control system is extremely important. A user interface will be developed to provide a summary of system performance to EVSE users and charging providers. Due to the potential for security risks when user interfaces are created, the entire system will be analyzed for cyber security risks. Appropriate security protocols will be implemented to avoid any possible risks.

## A. Instrumentation and Equipment Utilized for Study

The University of Louisville has 6 GE DuraStation Level 2 charging stations installed that will be utilized for this study [44]. The proposed control system will be implemented using these stations and wireless communication bridges will be developed for communication between nodes. The charging infrastructure is shown in figure 31. In addition to the GE charging stations, an interface for the utility meters on campus shown in Figure 32 will be developed for monitoring demand and energy consumption. Finally, the Siemens energy management system currently installed on the Belknap campus will be incorporated into the design to allow for monitoring and supervisory control of charging activity. Instrumentation located in the wireless design lab will be utilized when necessary for testing purposes. No other special instrumentation will be required.

FIGURE 31: GE DuraStation level 2 EVSE installed on UofL Belknap campus [58].

FIGURE 32: Louisville Gas and Electric utility meters installed on UofL Belknap campus.

## B. Data Analysis

Data collected throughout the study will be used to determine the feasibility and payback of an automated demand response system for PHEV charging in commercial environments. The data collected includes, but is not limited to, power and energy consumption for individual vehicles, weather data, campus-wide energy consumption, and cost of energy consumed during charging. Other data including the forecasted electrical demand and EVSE availability will be recorded for every demand interval. A database will be used to keep consumption and usage statistics for further development of prediction algorithms. This database will contain approximately 3 months of historical data for analysis, training of forecasting algorithms, and historical trending.

Analysis of data collected will be performed to verify the proper operation of the power monitoring and control system. Forecasted values for electrical demand and EVSE availability will be examined and compared to actual measured values. This will provide an accurate representation of the error of the power monitoring and control system as a single unit. This can be utilized to predict the resultant electrical cost increases due to the error. Additionally, the performance of the scheduling and prioritization algorithms will be analyzed to ensure that total processing times are minimized, therefore creating a fair charging environment. Data will also be analyzed to ensure that the power monitoring and control system adheres to the design objectives and hypothesis formulated in chapter I.

### C. Design Limitations

There are a number of challenges associated with the development and implementation of an automated demand response system for PHEV charging. The most significant challenge will be to develop a balance between system demand savings and charging performance. PHEV charging is highly inelastic due to limited electric range and EV owners' unwillingness to change charging habits if it affects their driving needs. This is a delicate balance that must be determined once data collection begins.

The second most important design challenge is to prevent peak demand increases so that the commercial time-of-day ratepayer, The University of Louisville in this instance, is not faced with high demand charges. This will require the development of a highly accurate demand forecasting algorithm to minimize control errors. If the system lacks precision and accuracy, proper control decisions cannot be made.

Other design challenges and limitations include real time data collection and analysis, providing on-time charging, and modular communication between nodes. Due to the differing types and manufacturers of electric vehicles available on the market, data collection and communication with each vehicle becomes difficult. A strategy will be developed to manage this issue. Additionally, various vehicles have different size battery systems. This is another factor that must be managed so that full charges can be obtained within adequate time. There are other limitations to such a design, but the few listed here are the most important issues that must be managed.

# CHAPTER IV

# DESIGN AND DEVELOPMENT OF POWER MONITORING AND CONTROL SYSTEM

Numerous case studies have been published in technical literature regarding the simulation of EV loads and the resultant effect on electric demand profiles and electric utilities [59], [60], [61], [62], [63]. These publications tend to focus on overarching effects of EV charging activity on large scale electric utility distribution systems and generation capabilities. The consensus from these articles is that without proper electrical infrastructure in place, the electric utility will face numerous problems as EVs grow in popularity. However, another problem exists on a smaller scale which is a direct consequence of the added electrical load from EV charging as shown in the problem statement of this dissertation. Whether EV charging activity takes place under residential or C&I rate structures affects the potential price of electricity that is consumed per charging transaction. Further, when EV charging takes place at work under C&I rate structures, the electricity cost can be significantly higher than under the residential rates due to the demand charge incurred by C&I ratepayers.

As a response to peak demand, Demand Side Management (DSM) has been shown to be an effective method of curtailing electric consumption during periods of peak electrical demand to improve power quality and reliability while preserving a specified level of service and comfort. The idea of DSM was first proposed by the

Electric Power Research Institute (EPRI) in the 1980s [64] and has slowly gained acceptance over time. However, with the recent inflow of EVs into the automobile market, EV charging loads have provided researchers and electric grid operators with a new tool when it comes to DSM. In fact, management of EV charging has become an entirely new subset of DSM as a whole. This dissertation proposes a novel and intelligent EV charging control framework that can be implemented in C&I locations to curtail the current disincentive for large scale EV adoption. More particularly, the restricted mileage range, or range anxiety, of EVs due to battery size is a common limiting factor in the decision to purchase such a vehicle as a primary mode of transportation. Many commercial electric ratepayers such as shopping centers, restaurants, schools, and businesses are installing EV charging infrastructure for patrons, customers, and employees to utilize in an effort to curtail the issue regarding range anxiety [65].

The design and development of an intelligent power monitoring and control system is paramount to the success of EV adoption in C&I environments. The overall goal of the Power Monitoring and Control System (PMCS) is to reduce EV charging load during peak demand periods. Therefore, reducing electric cost per-unit to the electric ratepayer. This section will detail the design and development of such a control system that can be implemented specifically for C&I electric ratepayers. First, an overview of the major system components will be presented. Next, a detailed description of data collection and management will be provided including the types of data collected, the frequency of data analysis and how this is implemented in the overall design. Following will be an in-depth description of the major subcomponents of the design: the data collection and management module, the demand forecasting module, the charging activity scheduling module, and the charging control component. Details about each major subcomponent will be presented along with the various options studied for each. Finally, a discussion will be provided regarding the design of the user interface for monitoring and control.

## A. Overview of Major System Components

The PMCS discussed here is composed of a few major components. Each component is designed to perform a specific task, which when combined with the other components, forms a much more advanced and complete control system. In this dissertation, the primary sub-components of the design are referred to as modules. These modules are as follows:

- Data collection and data management module
- Demand forecasting module
- EV charge scheduling and prioritization module
- Charging activity control module

Figure 33 shows the relationship between each of these modules and how each component fits into the overall power monitoring and control system design. Electrical demand is commonly measured in kilovolt-amps (kVA) and the readings are typically registered by the electric utility every 15 minutes. This time period is of great importance because the power monitoring and control system proposed and designed in this dissertation must accurately send control signals to on-line charging stations within that 15 minute period to prevent creating new demand peaks. Therefore, the modules depicted in Figure 33 operate in a cyclic fashion every 15 minutes.

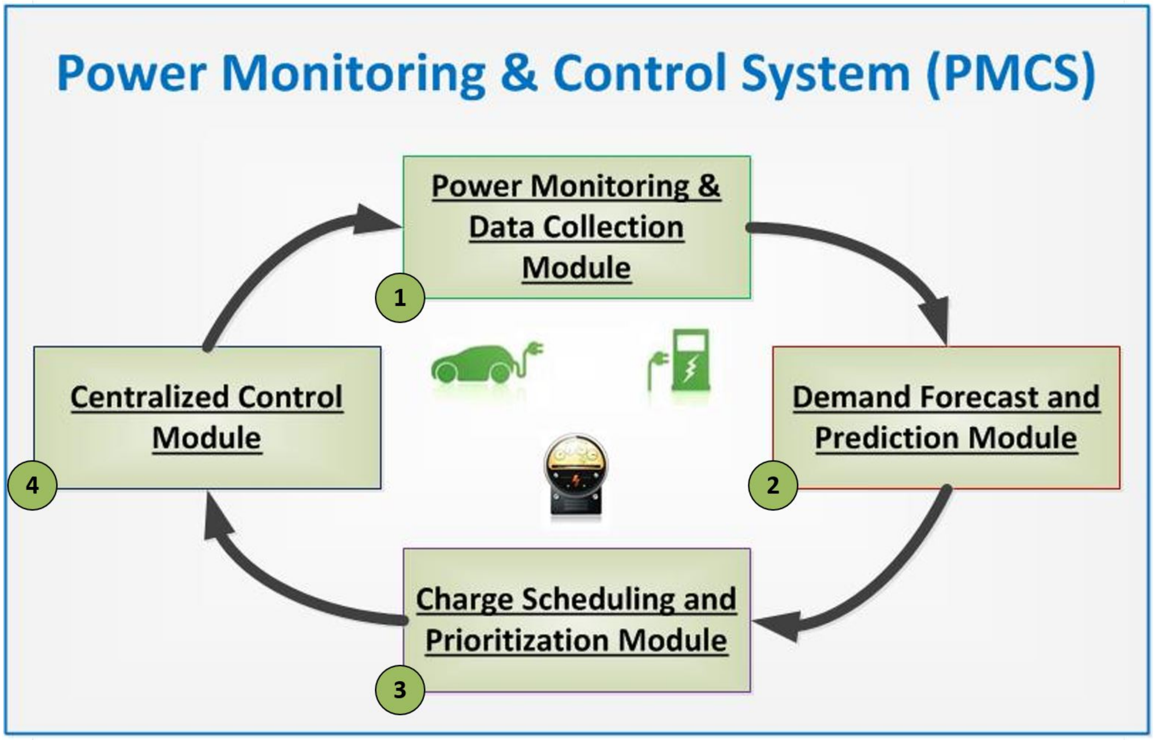



FIGURE 33: Relationship of PMCS modules to each other and to overall control system architecture.

Module #1 of the PMCS is responsible for real-time data collection from a variety of sources. This module communicates with the customers utility meter to collect energy and power data, the charging stations to determine energy usage and charging status. This module is also responsible for collecting weather data such as outside temperature and dew point which is utilized by the forecasting module to predict demand patterns. Finally, the data collection module also monitors the performance of the power monitoring and control system as a whole to verify control decisions and keep track of decision errors. Data storage is provided by the data collection module for historical data trending that is used to further refine the operation and performance of the PMCS throughout its lifetime.

Module #2, the demand forecasting module, then analyzes the data collected by module #1 and provides an accurate forecast of the expected electrical demand for the following 15 minute demand interval and also provides the expected number of charging stations that can be active without the possibility of driving a new demand peak. A number of forecasting methods were studied and a neural network forecasting model was chosen due to its high accuracy and train-ability. This also allowed the system to account for changes in demand due to weekends, holidays, and extreme events due to weather, as all of these affect the electrical demand of a typical commercial or industrial electric ratepayer [6].

Module #3 of the PMCS utilizes the data collected from vehicles, including state of charge (SOC) and time of arrival, and data provided by the demand forecasting module to schedule charging activity. By scheduling charging jobs, the total time it takes to charge all vehicles can be minimized in the event that there are more vehicles to charge than there are charging stations available. This can be the case if there is limited EVSE charging infrastructure installed at the point of charging, or if chargers must be shut off or disabled during peak demand periods [65]. Scheduling charging activity also provides a fair charging experience for all PHEV owners in that cars with higher SOC can be disabled or delayed if there is another vehicle plugged in that has a lower SOC. Scheduling can also account for cases where a charge cycle must be completed by a specified deadline.

Module #4 of the PMCS is responsible for using the forecasted data and the schedule provided to control the charging activity. This module communicates with the EVSE to enable / disable or even slow the charging rates on specific chargers. EVSE control is somewhat trivial due to its simplicity. The primary function of an EVSE is to switch an electrical contact, that can open or close, to control the flow of electrical power from the source to the vehicle. No power conversion takes place in the EVSE. Normally, the control circuitry in most EVSEs can accept a serial or ethernet data input to control the operation of the switch or contact inside. In the event that this control circuitry is not provided, a simple electrical contact could be added in series between the power source and the EVSE and controlled directly from the PMCS.

The following sections in this chapter will provide details for each of these modules that make up the PMCS. For each module, several algorithms were studied and examined. Data will be presented to justify the algorithms chosen.

## B. Data Collection and Management

The primary module of the power monitoring and control system outlined in this dissertation is module #1, the data collection and data management module. This module communicates with a number of devices to collect the data required to provide accurate forecasts and charging schedules resulting in optimal control of PHEV charging activity. In total, 9000 data entries are kept in the historical database at any one point in time, which is equivalent to 93.75 days or approximately 3 months of data. Each data entry contains the following: date stamp (month, day), time stamp (hours, minutes), day of the week (1-7), outside temperature (deg. F), outside dew point (deg. F), total electrical demand reading from utility meter (kW), previous meter reading (kW), and previous 2 hour average electrical demand (kW). Through experimentation, it was found that this data was sufficient for providing an accurate forecast of electrical demand. In addition, the output of the forecasting module is also stored in the database. These values include forecasted electrical demand for next 15 minute interval (kW), and forecasted number of chargers available. These values are used to verify the operation and accuracy of the forecasting algorithm and to keep track of events when charging must be disabled or shut off. Further information will be provided in the section detailing the forecasting module about these values.

Tables 6 and 7 represent a sampling of the data collected. Table 6 represents a cold Fall day in November where energy consumption is relatively low, therefore resulting in forecasted charger availability well over 100 chargers. Table 7, on the other hand, shows data collected during a hot Summer day in August. In this data, the energy consumption was high resulting in periods where some stations needed to be disabled and other periods where all charging had to be shut off to prevent driving new electrical demand peaks with the EVSE charging infrastructure.

Data is collected in a number of ways from the various sources. The date and time stamps are automatically generated from the data collection module for each data entry. Weather data and electrical demand values are gathered for this study from a Siemens energy management system located on the Belknap Campus at the

TABLE 6: Sample of data collected in November 2014.

| **Date** | | **Time** | | **Day of** | **Weather (deg. F)** | | **Electrical Demand** | | | **Forecasted Values** | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Month** | **Day** | **Hour** | **Min.** | **Week** | **Temp.** | **Dew Pt.** | **Present** | **Previous** | **2 Hr. Avg.** | **Demand** | **# of Chargers** |
| 11 | 13 | 12 | 0 | 5 | 28.9 | 21.66 | 7827.1 | 7901.2 | 7844.6125 | 7756.5580 | 184 |
| 11 | 13 | 12 | 15 | 5 | 29.6 | 21.81 | 7858.2 | 7827.1 | 7859.1125 | 7774.5132 | 178 |
| 11 | 13 | 12 | 30 | 5 | 29.7 | 22.16 | 7894.1 | 7858.2 | 7863.625 | 7897.6684 | 141 |
| 11 | 13 | 12 | 45 | 5 | 29 | 21.76 | 8018.2 | 7894.1 | 7862.7375 | 7939.7426 | 128 |
| 11 | 13 | 13 | 0 | 5 | 28.8 | 21.82 | 8107.1 | 8018.2 | 7882.375 | 7954.4671 | 124 |
| 11 | 13 | 13 | 15 | 5 | 28.2 | 21.49 | 7927 | 8107.1 | 7920.2625 | 7810.7188 | 167 |
| 11 | 13 | 13 | 30 | 5 | 28.3 | 22.07 | 8015.1 | 7927 | 7915.375 | 7879.5394 | 146 |
| 11 | 13 | 13 | 45 | 5 | 27.6 | 21.40 | 7903.1 | 8015.1 | 7943.5 | 7892.3428 | 142 |
| 11 | 13 | 14 | 0 | 5 | 27.7 | 21.73 | 7977.2 | 7903.1 | 7943.7375 | 7829.9608 | 161 |
| 11 | 13 | 14 | 15 | 5 | 28.2 | 21.97 | 8001.2 | 7977.2 | 7962.5 | 7881.8825 | 146 |
| 11 | 13 | 14 | 30 | 5 | 28.8 | 22.55 | 7992.1 | 8001.2 | 7980.375 | 7978.0485 | 116 |
| 11 | 13 | 14 | 45 | 5 | 28.3 | 21.83 | 7886.1 | 7992.1 | 7992.625 | 7735.7906 | 190 |

TABLE 7: Sample of data collected in August 2014.

| **Date** | | **Time** | | **Day of** | **Weather (deg. F)** | | **Electrical Demand** | | | **Forecasted Values** | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Month** | **Day** | **Hour** | **Min.** | **Week** | **Temp.** | **Dew Pt.** | **Present** | **Previous** | **2 Hr. Avg.** | **Demand** | **# of Chargers** |
| 8 | 27 | 11 | 0 | 4 | 85.4 | 77.33 | 12640.4 | 12195.5 | 12035.925 | 12466.4268 | 133 |
| 8 | 27 | 11 | 15 | 4 | 86.1 | 77.32 | 12643.5 | 12640.4 | 12149.5125 | 12614.9104 | 88 |
| 8 | 27 | 11 | 30 | 4 | 86.6 | 78.14 | 12589.3 | 12643.5 | 12236.8 | 12526.1937 | 114 |
| 8 | 27 | 11 | 45 | 4 | 87.1 | 78.61 | 12558.2 | 12589.3 | 12329.8125 | 12548.7616 | 108 |
| 8 | 27 | 12 | 0 | 4 | 87.8 | 78.58 | 12872.1 | 12558.2 | 12391.85 | 12715.4822 | 57 |
| 8 | 27 | 12 | 15 | 4 | 89.1 | 79.81 | 12717.7 | 12872.1 | 12493.4125 | 12908.5672 | 0 |
| 8 | 27 | 12 | 30 | 4 | 89.4 | 79.74 | 12859.8 | 12717.7 | 12560.0375 | 12847.5846 | 17 |
| 8 | 27 | 12 | 45 | 4 | 90.5 | 80.41 | 12874.2 | 12859.8 | 12634.5625 | 12966.9137 | 0 |
| 8 | 27 | 13 | 0 | 4 | 91.1 | 80.24 | 13028.7 | 12874.2 | 12719.4 | 13018.6016 | 3 |
| 8 | 27 | 13 | 15 | 4 | 92.1 | 80.02 | 13058.4 | 13028.7 | 12767.9375 | 12972.2690 | 26 |
| 8 | 27 | 13 | 30 | 4 | 93.6 | 80.61 | 13106.8 | 13058.4 | 12819.8 | 13168.0108 | 0 |
| 8 | 27 | 13 | 45 | 4 | 93.8 | 80.79 | 13043.7 | 13106.8 | 12884.4875 | 12950.2676 | 47 |

University of Louisville. The Siemens energy management software suite gathers data from a collection of sensors and transmitters located on the campus. The Siemens system also provides communication with the electric utility meters to retrieve energy consumption and electrical demand readings [66]. A screenshot of the University of Louisville Belknap Campus meter readings page from the Siemens Energy Management System is show in Figure 34.

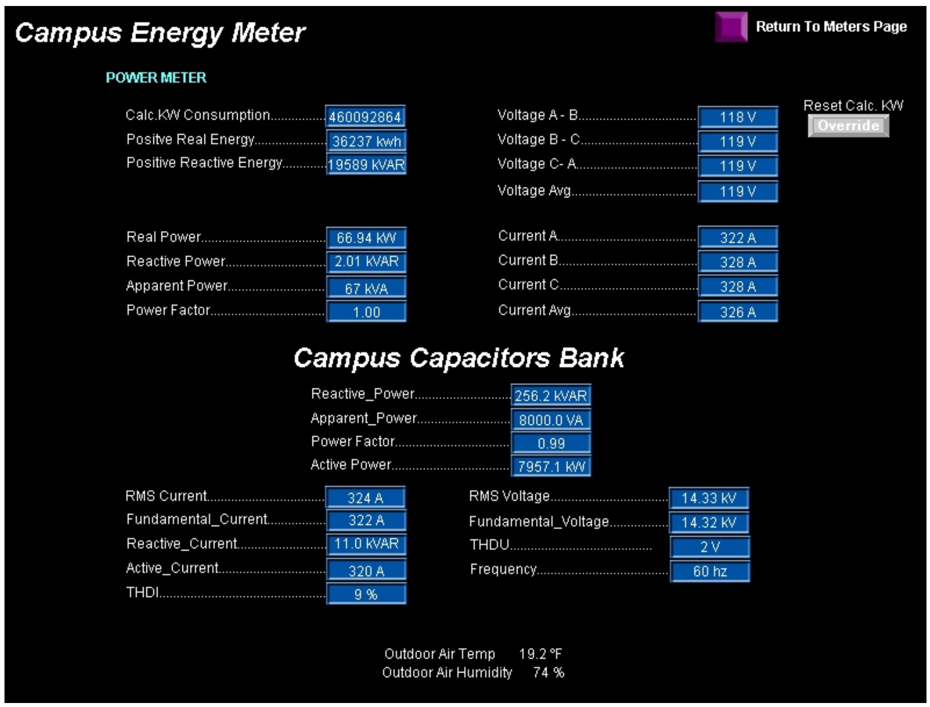



FIGURE 34: Siemens energy management system campus energy meter readings [66].

Due to the amount of data that is handled by the PMCS, Matlab r2012b [67] is utilized for implementation of the PMCS. Matlab is designed for handling matrices of data and also provides a great basis for implementing the data analysis, forecasting, and control algorithms. There are several useful tools available in the Matlab r2012b software suite including the web interfacing functions, neural network toolbox, control system toolbox, and general database management tools. Finally, Matlab also provides the capability to create stand-alone programs and custom user interfaces using m-files. The m-files created for the PMCS can be found in the Appendices of this dissertation.

In addition to the built-in functions pre-defined in Matlab, several functions were written to perform given tasks. The majority of data collected by the PMCS is gathered from the Siemens energy management system over a web interface. Typically, Matlab has a built-in function called *urlread* that can be used to pull HTML data from a given website. However, there are several shortfalls with *urlread*. The primary shortcoming is that *urlread* cannot access information on websites that are password protected. This is important to the PMCS because information on the Siemens energy management system is password protected. In order to resolve this issue, a new function *urlread_auth* was written combining code from the built-in Matlab *urlread* function and a more advanced *urlread* function written online [68] in response to some of the shortcomings of Matlab's built-in variant. Matlab's *urlread* function has a "params" argument, but these are CGI-style parameters that get encoded in the URL. Authentication is done with lower-level HTTP Request parameters. *urlread* doesn't support these, but you can code directly against the Java URL class to use them. The modified *urlread_auth* function can be found in Appendix I.

## C. Demand Forecasting

Typically, the demand profile for a given electric ratepayer is highly unpredictable. This varies for every electricity consumer, as some industrial ratepayers may have a flat demand profile, whereas commercial and residential ratepayers may have a more common load profile that has peaks and valleys throughout each day. The varying demand curve is normally due to human behavior. For example on a college campus, as people arrive, lights get turned on, air conditioning or heating loads come on to maintain building temperatures, computers boot up, etc... Due to the unpredictability and variability of the demand profile, an accurate forecast of this demand is paramount for the proper operation of a control system such as the one described here.

Module #2 of the PMCS provides peak prediction and load forecasting which is utilized to determine two primary values. These are the electrical demand forecasted for the subsequent 15 minute demand interval, and the number of electric vehicles that are allowed to charge during the subsequent 15 minute demand interval without driving the peak demand level higher for the current utility billing period. This allows for the scheduling and control modules of the PMCS to properly schedule charging activity so that demand peaks are avoided and charger availability is maximized.

Accurate forecasting of electrical demand has been a subject of much research due to its importance to electric utilities and how they schedule or dispatch generation capabilities. Forecasting methods can be broadly divided into two method types: statistical methods and artificial intelligence-based methods. In the case of the PMCS, both could be used to predict the electrical demand and resulting EV charger availability for each 15 minute demand interval. Statistical methods forecast current/peak loads by using previous load values in combination with a variety of exogenous variables such as weather, holidays, or other variables. Examples include similar-day, regression and time series methods [69]. Artificial Intelligence (AI) based forecasting techniques classify input data and associate it with respective forecasts and do not make use of the specific relations utilized in statistical methods. Examples of AI forecasting methods include neural networks and fuzzy logic [70]. This section will examine the behavior of both statistical and artificial intelligence forecasting techniques as they relate to the electrical demand forecasting problem. The Matlab software suite [67] is used to examine the training and output performance of the various forecasting methods studied. Figure 35 shows a typical flow diagram for analyzing a forecasting algorithm using Matlab.

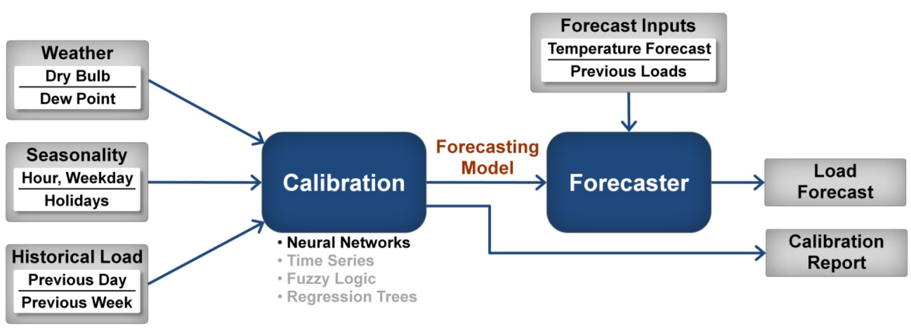



FIGURE 35: Typical flow diagram for analyzing forecasting methods using Matlab [71].

1. Development of Data Set for Forecasting Analyses

A major requirement for testing various forecasting algorithms is an extensive data set that can be used as inputs to a forecasting algorithm and also have sufficient data to verify the forecasted values. The initial data set used for this analysis was obtained from a number of sources including the University of Louisville Belknap campus, through the data collection module described previously, the local electric utility, and the National Oceanic and Atmospheric Administration (NOAA) Louisville weather station located near the University. The initial data set includes extensive data collected for a five month period ranging from July 12, 2010 to December 9, 2010. This time period was chosen because it contains the normal yearly demand peak for the University of Louisville. It also contains abnormalities in demand levels caused by extreme events such as weather (i.e. flooding, drought, extreme high/low temperatures, etc...) which may affect the performance of the forecasting algorithm. This data set was compiled by acquiring 15 minute demand data from the local electricity provider for 5 consecutive billing periods [50]. Data for kW demand, kVA demand and power factor were included in the database.

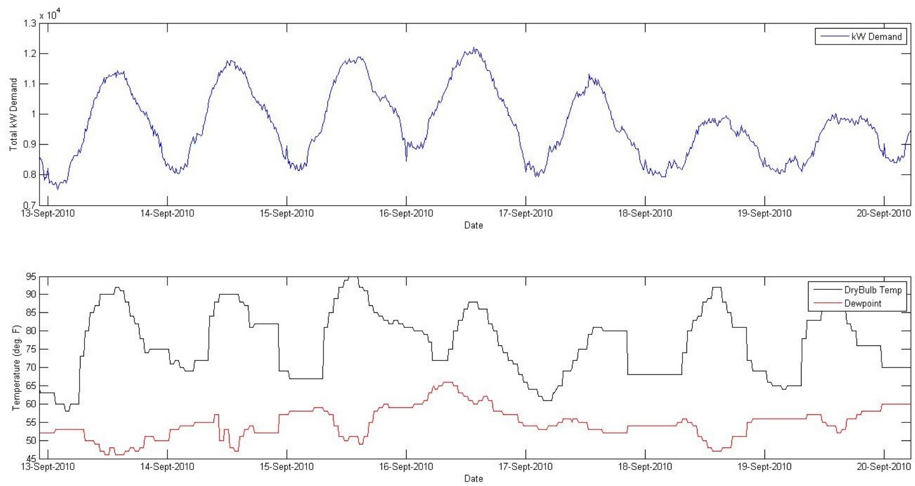



FIGURE 36: Plot showing electrical demand and temperature correlation [6].

Large commercial loads often correlate with weather patterns as shown in Figure 36. For example, peak electrical load in the summer occurs in the early afternoon when daily temperatures reach their peak. This is due to the electrical consumption of running air conditioners, refrigeration compressors and cooling towers. On the other hand, peak electrical demand during winter months occurs in the morning hours as people arrive to work, turn on lights and heat buildings. Figure 36 shows a plot of electrical demand (kW) and corresponding temperature measurements showing heavy correlation for one week in September 2010.

Although all of the data collected was not utilized in the final forecasting model, extensive weather data was accumulated to correspond with the 15 minute demand data collected from the utility due to this dramatic correlation between weather and electricity demand. The weather data was collected from the Louisville International Airport NOAA [72] weather station due to its proximity to the University of Louisville campus. The weather data collected included dry bulb temperature, dew point and wind speed with corresponding direction. In addition to the raw data collected from the aforementioned sources, a few additional auxiliary data fields were included in the database. These fields include a date and time stamp, day of the week, a holiday or weekend indicator, and a few data fields relating to the electrical demand measurements gathered from the utility. The supplemental demand data included: demand reading from the same 15 minute period from the previous day (24 hour delay), the rolling average demand from the previous 6 hours, and the prior 15 minute demand measurement. These additional data fields are used to refine the operation of the forecasting algorithms described and studied here. The overall data set was divided in half for training and testing of the various forecasting algorithms resulting in 7200 data points for training and 7200 data points for testing purposes. In the trials described here the input data set was kept the same to minimize variation and provide a good means to judge which forecasting algorithm provided the best results. Long term forecasts were calculated using the input data set and errors were calculated accordingly. The long-term forecasting technique was only used during initial analysis because analyses could be performed much faster. The actual implementation of the forecasting algorithm into the PMCS provides a short-term forecast every 15 minutes which results in much lower percentage errors.

After analysis of the forecasting methods, a new data set was formed through the data collection and management module of the PMCS. This data set only includes data necessary for successful operation of the forecasting algorithm chosen for implementation. Values such as wind speed and direction were discarded due to the negligible relation they share with electrical demand. This initial data set used during the primary study of various forecasting techniques is no longer utilized.

## 2. Review of Forecasting Techniques Studied

In previous research at the University of Louisville, researchers studied various forecasting algorithms including a simple extrapolation model, a previous week extrapolation model, and a regression forecasting model [73]. Each model was simulated using historical energy data from the University of Louisville. These three algorithms provided proof of concept and provided a basis for the work described here. Each algorithm studied had specific benefits, but no single forecasting algorithm provided optimal results. The work by Halbleib, et al. determined that the regression analysis forecasting model provided the best performance. However, the regression algorithm was also computationally intensive and still produced a significant forecasting error. A better solution was required for the PMCS. Several forecasting algorithms were considered throughout this study.

Building upon the work completed by Halbleib [73], the first forecasting algorithm studied was a multiple linear regression model. This model was found to provide the best performance of the algorithms tested by Halbleib. The linear regression model algorithm was studied here due to its simplicity and ease of calculation and tuning. Also there was room for improvement in performance due to the new data set used in this study, and linear regression forecasting models are commonly utilized for forecasting time series data sets. In the energy industry, linear regression models are commonly used to forecast electrical demand for generation dispatching

[74]. A least squares approach was used to find the corresponding coefficients for each of the input variables. After fine tuning, the linear regression model resulted in a $R^2$ value of 82.42%. This value is an improvement on the value found in the work by Halbleib, but that is due to the differing data set used as the input. Equation 4 shows the resultant linear regression model. This model provided a Mean Absolute Percent Error (MAPE) of 6.44% and a Mean Absolute Error (MAE) of 445.29 kW. However, the regression model could be calculated in approximately 1.19 seconds which is much faster compared to other algorithms tested.

$$\begin{aligned} kW_{forecast} = &-108.3 * (x_1) + 270.3 * (x_2) - 12.4 * (x_3) + 0.757 * (x_4) \\ &-24.7 * (x_5) + 16.8 * (x_6) + 0.452 * (x_7) + 0.683 * (x_8) \end{aligned} \tag{4}$$

- $x_1$: Day of Week (1 through 7)
- $x_2$: Weekend / Holiday Indicator (0 or 1)
- $x_3$: Hour (0 through 23)
- $x_4$: Minute (0, 15, 30, 45)
- $x_5$: Temperature (deg. F)
- $x_6$: Dew Point (deg. F)
- $x_7$: Previous day same interval demand (kW)
- $x_8$: Previous 6 hours average demand (kW)

Figure 37 shows the relation between the actual kW demand test values and the forecasted kW demand using the linear forecasting model. The model provided a good approximation of the kW demand for Tuesday through Friday, however there were significant errors on weekends and Mondays due to the extreme changes in demand for such days. This is also the case for holidays, however no holidays are shown in Figure 37. Possible improvements could be implemented in the input data set to provide a more accurate result in future trials such as providing a larger training data set or adding other input variables. However for simplicity, it was decided to keep the same input set for testing each forecasting algorithm.

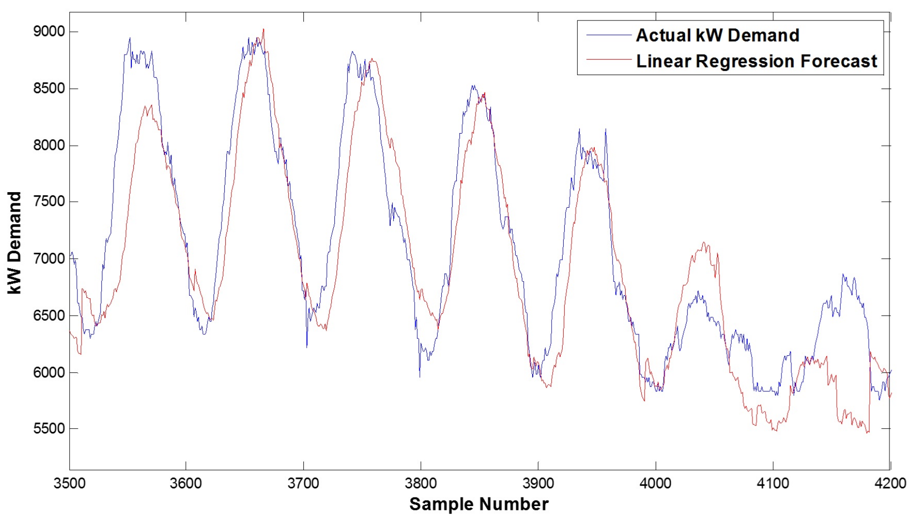



FIGURE 37: Performance of linear regression forecast algorithm for typical week [6].

The second forecasting method examined is a regression tree forecast. Regression trees are similar to decision trees, but instead of predicting a straightforward response from a finite set of values, the regression tree can output a continuous value, such as kW demand in the case of this application. Regression trees are calculated in a similar fashion to the linear regression model described previously. A regression tree is another common way of forecasting demand that builds a classification tree, when possible, based on the input variables such as temperature, dew point, time of day, day of week, etc This method provides a forecast by first building a regression tree with training data and then traversing through the tree and comparing input parameters until a leaf of the tree is reached. The value associated with the leaf is used to provide a forecasted value. The larger the tree or the more leaves included in the tree design result in more accurate outputs. Regression tree analyses are commonly used for long term approximation and forecasting, but can also be used for short term forecasts as well [75]. In this analysis, several regression trees were formed and then combined and used to forecast kW demand levels using the test data set with Matlab software [67]. Mixed results were achieved in this analysis and can be seen in Figure 38. The largest errors in the predicted values occurred on weekends, however significant errors were encountered during weekdays as well. The regression tree method provided a MAPE of 19.22% and a MAE of 1184.33 kW while using 20 bagged trees and the input data set defined previously. Most of the error shown in Figure 38 is a result of overtraining the regression tree model. This could be avoided, however for testing purposes, the same input data set was used in each forecasting analysis. Electrical demand is not typically constant over the long term, i.e. months or a year, due to variations in the seasons. Large variations in demand cause the regression tree analysis to produce erroneous forecasts, which is the case for the test data set used in the analysis of this algorithm. This method took approximately 23.5 seconds to train, which is slightly longer than the linear regression method. Changing the number of trees did not affect the MAPE or MAE as these values stayed somewhat constant. Better performance could be achieved by adjusting the data set, which is also the case for the linear regression model.

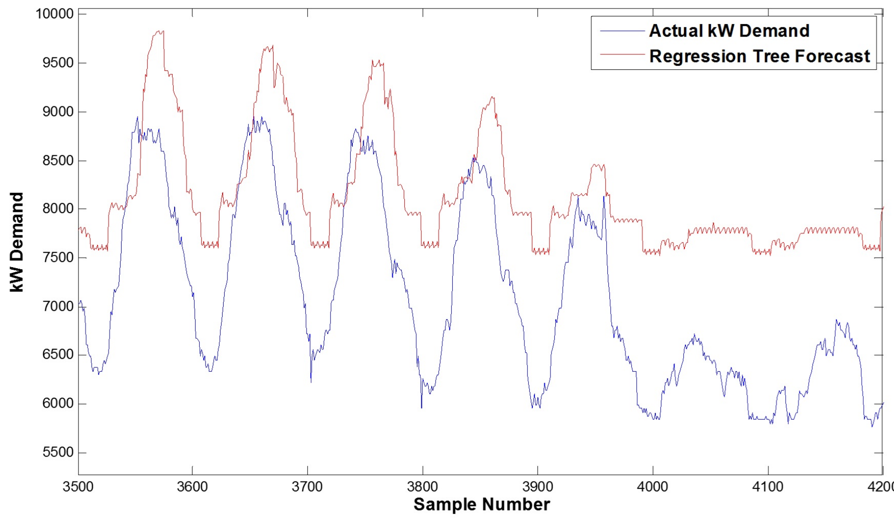



FIGURE 38: Performance of regression tree forecast algorithm for typical week [6].

The data and predictors supplied in these forecasting trials are highly non-linear as seen in the results found with the linear regression and regression tree approaches. Electrical demand not only varies throughout the course of a day but also changes drastically over the course of a year. For example, the data collected in Tables 6 and 7 show how the demand varies from a hot summer month and a cooler winter month. Demand varied in those tables from 13MW to 7MW between seasons. Therefore, traditional statistical linear models may not be adequate for providing an accurate forecast of demand. Due to the difficulty of determining an adequate characteristic equation for a non-linear model such as an electricity demand curve, an artificial intelligence forecasting technique was examined. L. Wang [76] and Ghanbari, et al [77]. have shown through research that optimal forecasting models can be achieved using neural network approaches. The neural network developed in this study was simulated with a varying number of hidden nodes. Matlabs neural network toolbox [67] was used to quickly train and test the performance of the neural networks.

Preliminary tests of the neural network design were simulated using: date, day of week, holiday/weekend indication, temperature, and dew point data to predict the corresponding load. These tests provided promising results, but there was considerable room for improvement. Preliminary tests provided MAPEs ranging from 6% to 8% depending on the number of hidden nodes used. Additionally, the neural network models only took approximately 30 to 45 seconds to train which would still be acceptable for the PMCS.

In an attempt to further improve the performance of the neural network time series prediction, the input data fields were changed. Subsequent tests based the demand forecast on the following input data fields: day of week, holiday/weekend indicator, hour, minute, temperature, dew point, previous 6 hour average load, and previous day same demand interval load. These were the same 8 data fields used for the linear regression and regression tree analyses. The updated data fields provided much better performance. The best performance of the neural network model was achieved by using 30 hidden nodes resulting in a MAPE of only 1.77% and a MAE of 145.4 kW. Calculation time was approximately 57 seconds. These results are much more favorable for use with the PMCS. The forecasted demand closely follows the actual demand measured, but minor errors occur at the peaks for each day as shown in Figure 39. This could be corrected by increasing the number of hidden nodes or adding input data to the system.

Finally, in an attempt to minimize peak prediction errors associated with the neural network model without modifying input data, an averaging function was added. This function takes the forecasted demand and averages that value with the actual kW demand from the previous measured interval. The addition of this algorithm minimizes peak overshoot and peak undershoot of the forecasted demand with respect to the actual measured demand. The smoothing action of the averaging function resulted in an adjusted MAPE of 1.26% and a MAE of 86.01kW. The results of the averaging function can also be seen in Figure 39. The improvement in forecasting error is visible when compared to the actual demand value measured. Although 1.26% MAPE is very good when compared to the other forecasting methods, it still shows room for improvement. In the event that PHEV charging demand is less than the accuracy of the forecasting method, some errors can occur resulting in increased demand peaks or higher electrical cost per unit for the C&I electric ratepayer.

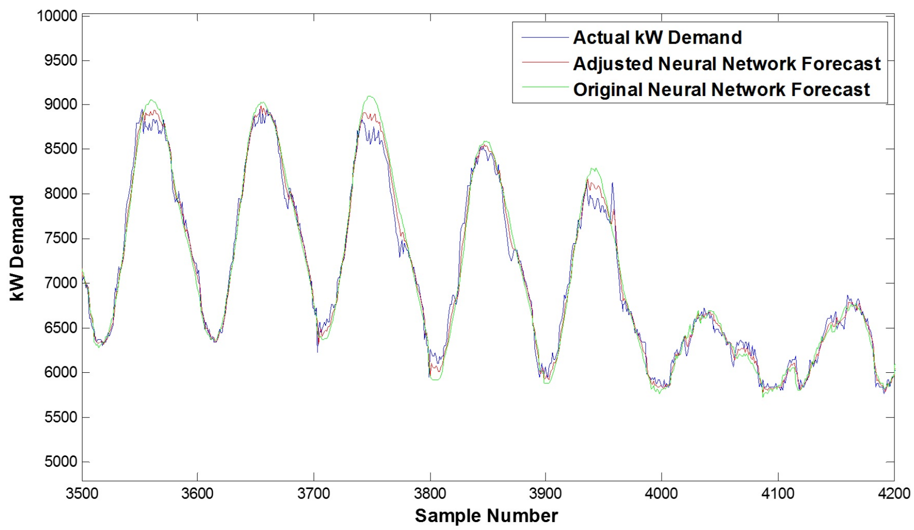



FIGURE 39: Performance of neural network forecast algorithm for typical week [6].

### 3. Selection and Implementation of Neural Network Forecasting

If an accurate non-linear model can be developed, then the calculation time and error may be greatly reduced by using a non-linear regression analysis technique. The varying nature of electrical demand limits the accuracy that is possible by a linear regression model. However, since the PMCS only requires a forecast to be generated every 15 minutes for the ensuing demand interval, calculation time becomes a non-factor in the design choice. Through analysis, disregarding calculation and training time, the best solution has been determined to be the neural network option due to its accuracy and forecasting performance. The calculation and training time is much longer for the neural network model, but overall performance is much better than other algorithms studied.

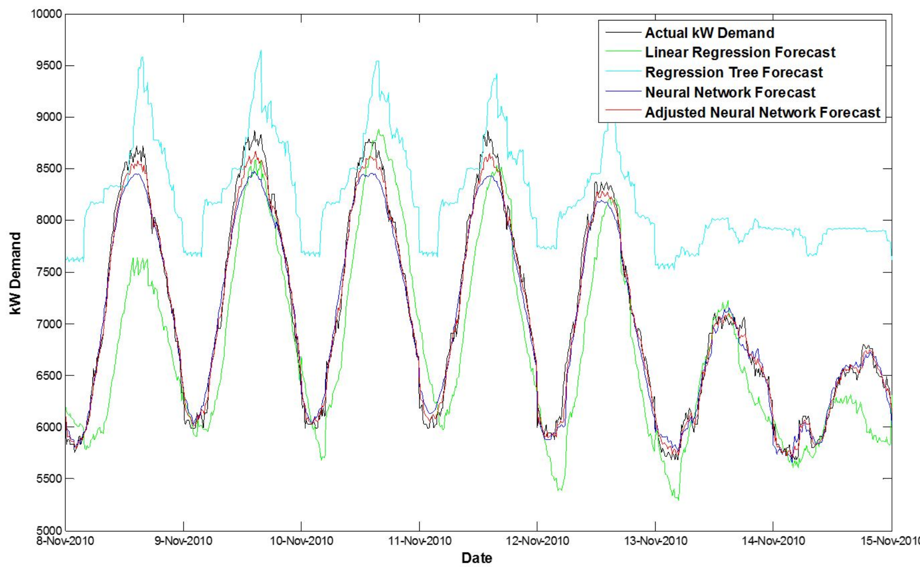



FIGURE 40: Forecasting algorithm performance.

Figure 40 represents a compilation of the three types of forecasting algorithms analyzed in this study. The neural network forecast model with an averaging function added provides the best approximation of the actual kW measured demand for the same period. Table 8 summarizes the characteristics of the forecasting models tested. The simulations run in this study provided a long-term prediction for a 2.5 month period, however when integrated into the PMCS the forecast algorithm provides a short-term forecast for every 15 minute demand period. By re-training the forecasting algorithm every 15 minutes, more accurate results are achieved. Errors represented by the MAE and MAPE in Table 8 will be further reduced by forecasting the short term 15 minute demand as compared to the 2.5 month long term period forecasted in these trials.

Each forecasting algorithm developed and simulated in this study was also tested for performance after implementation into the PMCS. Forecasting models were

TABLE 8

Performance of Forecasting Algorithms.

| **Forecast Model** | **MAE (kW)** | **MAPE (%)** | **Train Time (sec)** |
|---|---|---|---|
| Linear Regression | 445.29 | 6.44 | 1.19 |
| Regression Tree (20 trees) | 1184.33 | 19.22 | 23.5 |
| Regression Tree (50 trees) | 1233.02 | 19.94 | 58.19 |
| Neural Network (30 Hidden Nodes) | 145.40 | 1.77 | 57 |
| Neural Network (w/ Averaging) | 86.01 | 1.26 | 57 |

compared on two primary performance factors including demand cost increase (in US dollars) and charging downtime (hours per day). The optimum system should have minimal cost increases while also minimizing time throughout the day when charging must be completely disabled. The increase in cost was calculated by taking the MAE of each forecasting model and finding the resultant increase in cost if this error occurred during the peak demand period. Total time that charging activity is halted was calculated based on the assumption that the control system halts charging when a new demand peak is forecasted for the billing period. The total time in which charging was disabled temporarily was accumulated for each billing period of test data. An average was then calculated for each forecasting algorithm modeled. The results for the three forecasting algorithms tested in this study along with three other methods studied are depicted in Figure 41. The most favorable forecast method will be located in the bottom left corner of the plot. This plot also includes forecasting algorithms studied in research by Halbleib, et al [73].

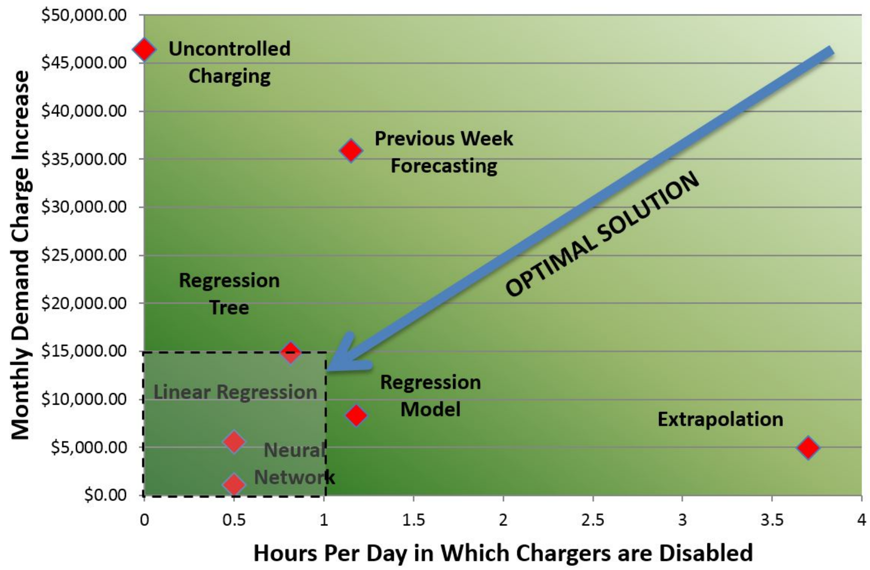



FIGURE 41: Forecasting algorithm performance as tested after implementation in PMCS.

From Figure 41, it can be seen that the neural network forecasting method provided the optimal performance for a worst case scenario. Therefore, the neural network forecasting method was chosen for the PMCS. Further experimentation and fine tuning were performed on the neural network forecasting algorithm. The input data set used for training the neural network forecasting algorithm was slightly changed. The algorithm still uses date and time stamps, temperature, dew point, and present electrical demand, however the auxiliary inputs were modified slightly due to the change from a long-term to short-term forecast. The forecasting algorithm now uses the previous 15 minute electrical demand reading, and a running 2 hour average electrical demand calculation as shown in Tables 6 and 7.

Using the data collected and managed by the data collection and management module of the PMCS, more accurate electrical demand forecasts can be achieved. The neural network is now re-trained every 15 minutes using the 9000 data points stored in the historical database. Using the neural network model, a forecast for the ensuing 15 minute demand interval is calculated. MAPE is greatly improved by switching from the long-term forecast to the short-term forecast. New MAPE values of approximately 0.02% have been achieved using the new forecasting model. Figure 42 shows the improvement in MAPE for approximately 1600 data points recorded during testing of the forecasting algorithm. The improved performance of the new neural network forecasting algorithm result in better performance than the best algorithms shown in Table 8 and Figure 41.

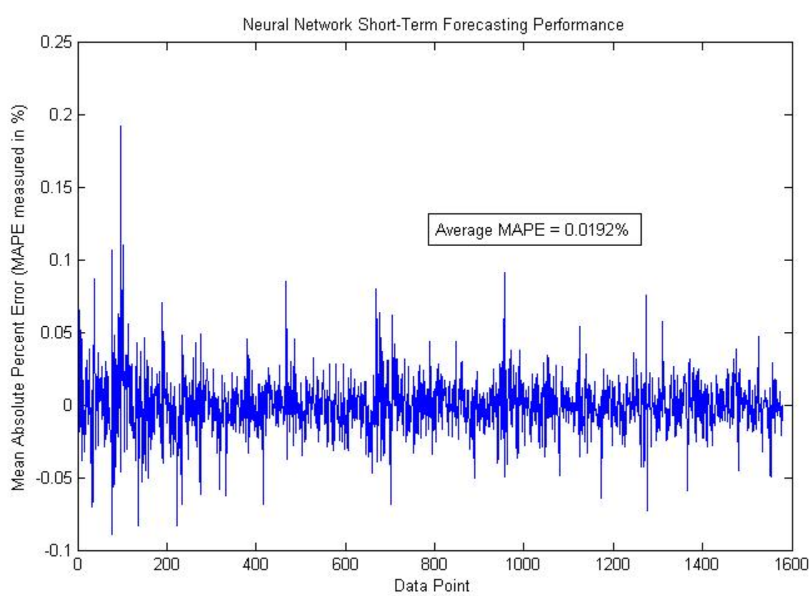



FIGURE 42: Forecasting algorithm percentage error for short-term forecast.

In addition to providing an accurate forecast for the electrical demand expected for the following 15 minute demand interval, the PMCS forecasting module also provides a forecast of the number of EVSEs that can be active during the next demand interval without the possibility of creating a new demand peak. This is calculated by keeping track of the peak demand for the billing period and comparing it to the forecasted electrical demand value. Since level II EV chargers consume a constant 3.3kW of electrical demand when charging, the number of EVSEs that can be active is calculated by dividing the difference between maximum and forecasted electrical demand by 3.3. Keeping track of the peak demand for the billing period has proven to be a difficult task. In most electrical billing structures [1] a minimum demand charge can be encountered. This is typically 50% to 75% of the maximum demand over the previous 11 months of billing data. In order to account for this, the PMCS forecasting module keeps track of the maximum demand for the present billing period. At the start of a new billing period, the PMCS sets the maximum electrical demand value to 75% of the maximum value measured in the previous billing period. Matlab code written to implement the neural network forecasting method can be found in Appendix II.

### D. Charge Scheduling and Prioritization

The control system discussed here may limit the number of EV chargers available for a given period of time in order to deal with the demand charge faced by C&I ratepayers. When charging activity is limited, a number of charging stations are disabled. This gives rise to situations where there are more vehicles requiring a charge than there are EV charging stations available. Consequently, this results in the need to prioritize the EV charging process and the necessity of intelligent scheduling to optimize the charging experience for all EVs. In scenarios where there is limited charger availability, the total processing time for all charging jobs rises. This section describes the third module of the power monitoring and control framework which is comprised of a machine scheduling algorithm. The flowchart shown in Figure 43 represents how the scheduling component fits within the overarching PMCS framework.

This section formally introduces the EV scheduling problem with charger availability constraints. First, a simple prioritization algorithm is developed that determines which charging stations are disabled when charging activity is limited, but not completely disabled. Next, for the possible scenario where there are many more EVs requiring charge than there are charging stations available, a scheduling algorithm is developed that can be implemented to minimize the total processing time required for all jobs. Four heuristic methods for solving the EV charge scheduling problem are proposed and evaluated for implementation into the PMCS. The optimal solution for the scheduling problem is proposed and considerations are made concerning how it is implemented into the PMCS design.

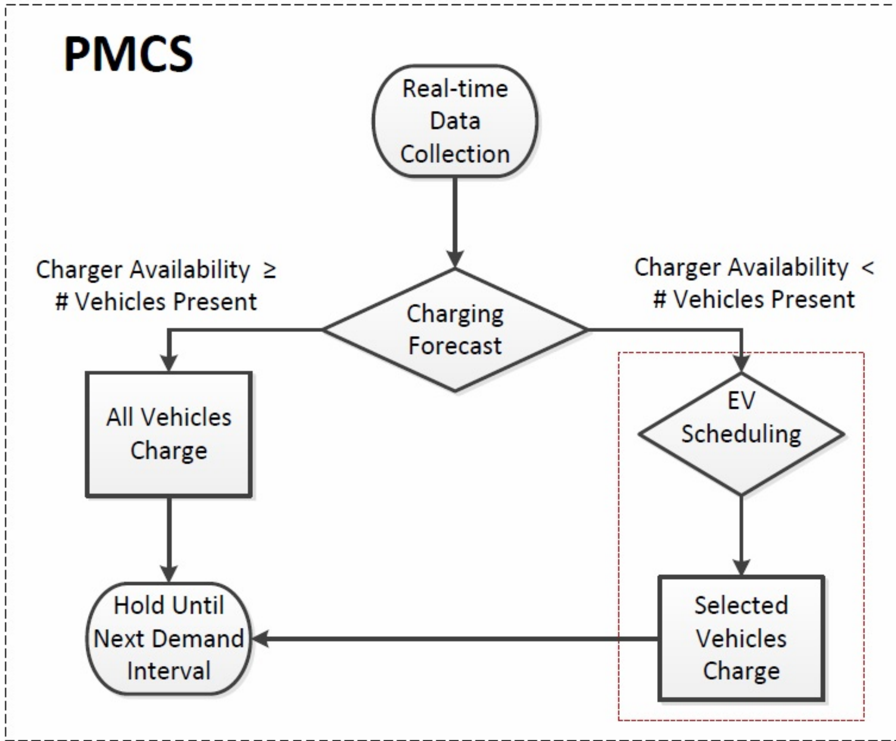



FIGURE 43: PMCS flowchart highlighting the scheduling and prioritization module.

1. Prioritization of Charging Jobs

In most cases, the need for a scheduling algorithm does not exist. Instead, a simple prioritization model can be formulated to assign charging priority to vehicles that are currently connected and charging. The lack of need for a scheduling algorithm is due to the fact that most commercial charging providers will have available charging infrastructure to accommodate all EV owners wishing to charge their vehicles. When charging capacities are limited due to an approaching electrical demand peak, but not fully disabled, a priority must be assigned to existing vehicles to determine which charging jobs to temporarily disable.

The prioritization algorithm utilized by the PMCS communicates with each vehicle connected through its OBDII diagnostic port to determine vehicle state of charge. Once the state of charge has been determined for every vehicle connected and charging, a priority list can be formed. Higher charging priority is given to vehicles with lower state of charge. Consequently, lower priority is given to EVs with a higher state of charge. If a subset of chargers must be disabled, charging is disabled for vehicles with lower charging priority first. The result of this algorithm provides a fair charging experience for all vehicles connected as it allows vehicles with longer processing times to remain connected when possible. If vehicles have similar states of charge, charging priority is given to the vehicle that arrived first. Figure 44 shows an example of three vehicles with varying states of charge. The priority assigned to each vehicle is shown.

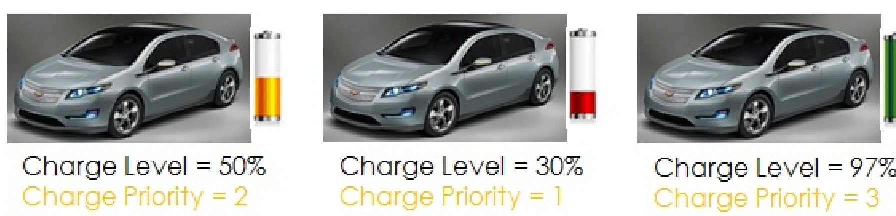



FIGURE 44: Prioritization of EV charging jobs based on vehicle state of charge.

## 2. Review of Machine Scheduling

The case rarely exists where the number of EVs exceeds the number of EVSE available by a margin large enough to call for a scheduling algorithm. One example of such a scenario would be a rental car company that rents EVs to customers but only has a limited number of charging stations available for returned vehicles. Assuming the rental company has 80 electric vehicles and only 20 charging stations installed, a scheduling algorithm can be formulated to minimize the total processing time to complete a charge cycle on all vehicles. A scheduling solution was presented in [65] that can be implemented to minimize the total processing time required. The following is a summary of the findings [65].

The problem of scheduling the EV charging process is a centralized optimization problem and can be formulated as a parallel machine scheduling problem. In this problem, charging stations represent similar parallel "machines" and the EVs requiring charge represent "jobs." The objective of the optimization process is to minimize the total processing time, or makespan, to complete all charging jobs. To facilitate the machine scheduling formulation of the EV charging problem in this section, $m$ represents the number of charging stations available and $n$ represents the number of jobs. Four scheduling algorithms were developed with the intent to optimize the charging schedule to minimize total makespan. A mixed integer programming (MIP) model was developed as well to verify the various scheduling algorithms developed.

### 3. Scheduling Methods Studied

Four scheduling algorithms were developed and simulated, each being used in one of two variants: preemptive and non-preemptive scheduling. In non-preemptive scheduling algorithms, a forecast is developed for the number of machines available and various machines are marked as disabled for given demand periods. Jobs are then scheduled to the machines' available time slots ensuring that the jobs do not overlap the disabled periods. Further, jobs that would overlap are scheduled at the end of the down time or on the next available machine. Preemptive scheduling algorithms are similar, however jobs can be scheduled if they overlap with demand intervals. When an overlap occurs on the schedule, the overlapping job is paused for the duration of the interval and then resumes when the demand interval has passed.

The preemptive and non-preemptive variants of the 4 scheduling algorithms were coded using Matlab software [67] for simulation purposes. The MIP model used for algorithm verification was developed in CPLEX [78]. CPLEX is an iterative program commonly used in optimization problems that can determine the optimum solution for small data sets. CPLEX is not optimal for scheduling EV charging activity with large data sets since computation times increase exponentially as the number of vehicles or charging stations rises. The four scheduling algorithms considered are listed here:

- The First Available Scheduling Algorithm (FAS)
- The Random and First Available Scheduling Algorithm (RFAS)
- Greedy Local Search Algorithm with Pairwise Exchange (GLS)
- Simulated Annealing Algorithm with Pairwise Exchange (SA)

The First Available Scheduling Algorithm (FAS)

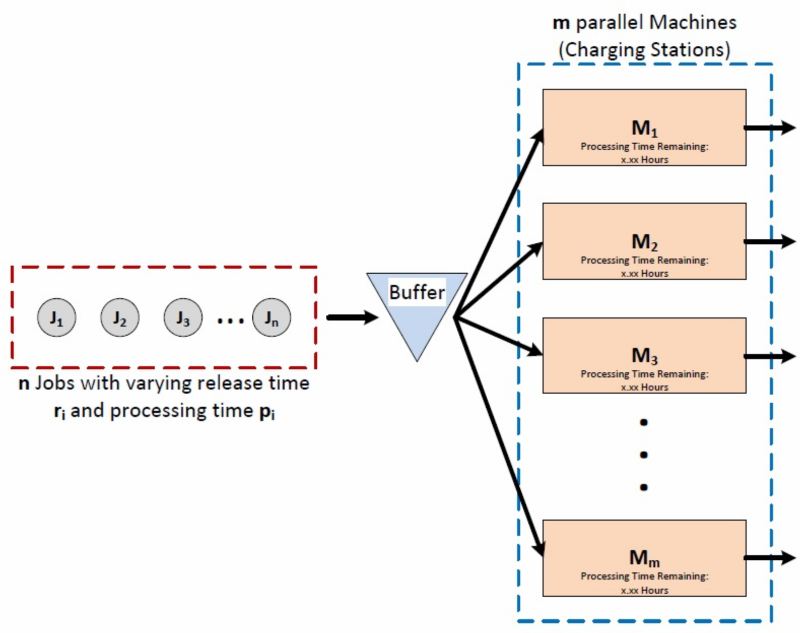



FIGURE 45: First available scheduling (FAS) algorithm diagram.

The First Available Scheduling (FAS) algorithm determines the charging schedule by simulating a typical EV owner's behavior of searching for the next available machine, as illustrated in Figure 45. In this algorithm jobs are sorted first by processing time required $p_i$ (longest to shortest) and then by job arrival time $r_i$ (earliest first). This sorting process gives priority to jobs with longer processing times $p_i > p_j$ when jobs have equal release times, and gives priority to jobs with earlier release times $r_i < r_j$ otherwise. After sorting jobs, jobs are scheduled to the next available machine based upon the total processing time $p_i$ remaining on each EVSE. All jobs are scheduled in this fashion until no jobs remain to be scheduled. The pseudo code for the FAS algorithm is described in 4 simple steps:

**Step 1)** Sort all jobs by processing time required $p_i$ and then by release time $r_i$.

**Step 2)** Calculate completion time $c_i = r_i + p_i$ for each machine.

**Step 3)** Schedule next job $j_i$ on priority list to machine with earliest completion time $c_i$.

**Step 4)** Repeat steps 2 and 3 until all jobs are scheduled.

The Random and First Available Scheduling Algorithm (RFAS)

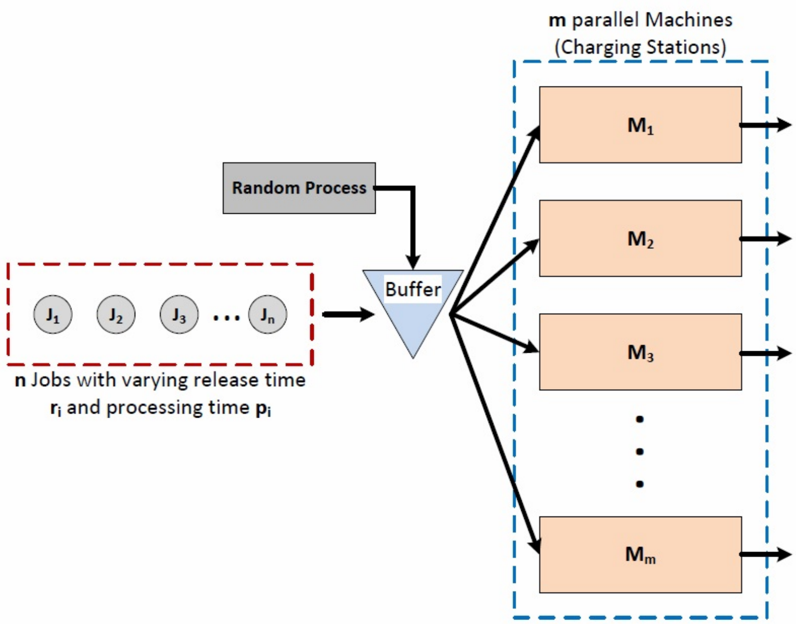



FIGURE 46: Random and first available scheduling (RFAS) algorithm diagram.

The Random and First Available Scheduling (RFAS) algorithm attempts to improve upon the performance of the FAS algorithm by adding in a randomization factor. This algorithm takes advantage of the fact that not all charging jobs are similar. By scheduling randomly selected jobs on a random machine rather than the next available, reductions in total processing time are possible. Figure 46 represents how the RFAS algorithm is similar to the FAS algorithm, but a random process is implemented to potentially minimize total makespan. In the RFAS algorithm, $R_{max} = 100$ schedules are generated and the schedule with the best makespan is selected as the heuristic solution. The following 6 steps define the basic operation of the RFAS algorithm:

**Step 1)** Sort all jobs by processing time required $p_i$ and then by release time $r_i$.

**Step 2)** Calculate completion time $c_i = r_i + p_i$ for each machine.

**Step 3)** If a Bernoulli random variable = 1, schedule job to random machine $m_i$, otherwise schedule next job on priority list to machine with earliest completion time $c_i$.

**Step 4)** Repeat steps 2 and 3 until all jobs are scheduled.

**Step 5)** Repeat steps 1 through 4 to generate $R_{max}$ random schedules.

**Step 6)** Compare schedules and select the schedule with smallest total makespan.

## Greedy Local Search Algorithm with Pairwise Exchange (GLS)

The third scheduling algorithm developed is the Greedy Local Search (GLS) algorithm. It starts with the optimum schedule obtained from the RFAS algorithm then performs a pairwise exchange optimization sequence. The pairwise exchange process begins by randomly picking two jobs ($J_i$ and $J_j$) from two random machines ($M_k$ and $M_l$) and checks to see if an exchange is feasible. Assuming the job exchange is feasible, the exchange is made temporarily and the total makespan is calculated. If the makespan decreases, then the exchange is kept. However if the total makespan increases, the exchange is reverted and discarded. The pairwise exchange process is repeated for $G_{max}$=10000 iterations. The GLS algorithm can be described in the following pseudo code:

**Step 1)** Begin with best schedule from the RFAS algorithm.

**Step 2)** Pick two random jobs ($J_i$ and $J_j$) from two random machines ($M_k$ and $M_l$)

**Step 3)** Check feasibility of exchange $r_i < s_j$ and $r_j < s_i$.

**Step 4)** If exchange results in reduced makespan, keep exchange. Otherwise discard.

**Step 5)** Repeat Steps 2 through 4 $G_{max}$ times.

## Simulated Annealing Algorithm with Pairwise Exchange (SA)

Finally, the last scheduling algorithm developed is the Simulated Annealing (SA) metaheuristic. This has been studied extensively [79],[80] and shown to be efficient in finding the global optimum of highly non-linear problems and/or many classes of combinatorial optimization problems. Through several trials, the other three algorithms studied often located local minima instead of the global optimal solution. The SA algorithm operates by developing an exponential cooling schedule to determine the probability of accepting an exchange, even when the exchange may not result in a reduction of the total makespan. The probability of accepting a bad move at temperature $T_i$ is determined by Equation (5) where $mkspn'$ is the new calculated makespan and $mkspn$ is the current makespan prior to the job swap.

$$P(mkspn, mkspn^{'}, T_i) = \begin{cases} 1 & \text{if } mkspn^{'} < mkspn \\ e^{\dfrac{-(mkspn^{'} - mkspn)}{T_i}} & \text{if otherwise} \end{cases} \tag{5}$$

The exponential cooling schedule represented by Equation (6) is chosen to allow unintended exchanges with higher probability at the start of the algorithm, but this probability decreases as the simulated annealing process progresses. For the EV scheduling problem, an exponential cooling schedule was chosen with a starting temperature $T_0$ of 15, which is slightly higher than the average makespan of all test runs from the other three algorithms. The temperature at iteration $i$ is updated using Equation (6) for each iteration $i$=1..N of the SA metaheuristic. An exponential reduction coefficient of A=0.36 was chosen using Equation (7) as a guideline resulting in $\alpha$=0.7 for the problem. The number of iterations in simulation results presented for the SA algorithm was chosen to be $S_{max}$=10000 based on performance and required CPU time.

$$T_i = T_0 * e^{(-A*i)} \tag{6}$$

$$A = \frac{1}{N} * \ln \frac{T_0}{T_N} \tag{7}$$

The pseudo code of the SA algorithm is as follows:

**Step 1)** Begin with best schedule from the RFAS algorithm.

**Step 2)** Pick two random jobs ($J_i$ and $J_j$) from two random machines ($M_k$ and $M_l$)

**Step 3)** Check feasibility of exchange $r_i < s_j$ and $r_j < s_i$.

**Step 4)** Update simulated annealing temperature $T_i$.

**Step 5)** If $mkspn' < mkspn$, keep change, else if $P(mkspn, mkspn', T_i) < rand(n)$

keep change, otherwise discard.

**Step 6)** Repeat steps 2 through 5 $S_{max}$ times.

4. Selection of Off-line Simulated Annealing Method

Performance of the 4 scheduling algorithms was judged based on a test data set developed to mimic real-life arrival and departure patterns of vehicles on a college campus. Normal distributions of job release times (vehicle arrival time) and processing times (state of charge required) were generated for all test cases. These normal distributions were centered on 11:00am and 45% state of charge respectively, and were based on vehicle arrival patterns and average commuter distances at the University of Louisville. The Chevrolet Volt [12] was used as the model vehicle in the test data. Test data was generated for the cases shown in Table 9, where the number of vehicles and charging stations range from 10 to 80, and from 3 to 20, respectively. Charging station availability was determined from the neural network forecasting algorithm developed for the forecasting module of the PMCS. Due to excessive processing times, the MIP model developed to be solved in CPLEX was only solved for case numbers 1 and 2 as shown in Table 9.

A summary showing the average makespans and CPU times for the simulations can be seen in Tables 10 & 11. Table 10 reports average makespans of ten data sets for each case shown in Table 9. Comparing non-preemptive to preemptive models, reductions in the total makespan are visible due to the elimination of idle time on machines when jobs overlap with peak demand intervals. SA algorithms tend to

TABLE 9

Description of test data sets generated for simulation.

| Case # | # Vehicles (Jobs) | # Charging Stations (Machines) | # Data Sets Available |
|---|---|---|---|
| 1 | 10 | 3 | 10 |
| 2 | 10 | 5 | 10 |
| 3 | 15 | 3 | 10 |
| 4 | 15 | 5 | 10 |
| 5 | 20 | 6 | 10 |
| 6 | 80 | 20 | 10 |

provide better performance for cases where the vehicle to charging station ratios are higher, however cases with lower vehicle to charging station ratios tend to see better performance from the GLS algorithms. Table 11 presents averages of CPU times for ten data sets for each of the six scenarios simulated. As the algorithm complexity increases, the resultant CPU time required also increases proportionally. Also, it is observed that the preemptive algorithms require approximately double the CPU time required for similar non-preemptive algorithms. This is due to the computational complexity of the preemptive algorithms since these must continually adjust processing times for all affected jobs when a pairwise exchange is made.

TABLE 10

Summary of average makespan objective (in hours) for all algorithms.

| **Heuristic** (NP=non-preemptive P=preemptive) | **Case 1** n=10 m=3 | **Case 2** n=10 m=5 | **Case 3** n=15 m=3 | **Case 4** n=15 m=5 | **Case 5** n=20 m=6 | **Case 6** n=80 m=20 |
|---|---|---|---|---|---|---|
| FAS (NP) | 11.090 | 10.476 | 14.981 | 12.092 | 11.616 | 14.083 |
| RFAS (NP) | 10.228 | 8.993 | 13.802 | 11.349 | 10.906 | 13.848 |
| GLS (NP) | 10.393 | 8.942 | 13.731 | 11.411 | 10.654 | 12.281 |
| SA (NP) | 10.387 | 9.022 | 13.707 | 11.212 | 10.761 | 12.947 |
| FAS (P) | 10.119 | 9.009 | 13.526 | 11.117 | 10.309 | 12.597 |
| RFAS (P) | 10.119 | 9.009 | 13.526 | 11.117 | 10.180 | 12.597 |
| GLS (P) | 9.406 | 8.254 | 12.871 | 10.389 | 9.931 | 11.848 |
| SA (P) | 9.501 | 8.400 | 12.852 | 10.379 | 9.895 | 11.801 |

TABLE 11

Summary of average CPU time (in seconds) for all algorithms.

| **Heuristic** (NP=non-preemptive P=preemptive) | **Case 1** n=10 m=3 | **Case 2** n=10 m=5 | **Case 3** n=15 m=3 | **Case 4** n=15 m=5 | **Case 5** n=20 m=6 | **Case 6** n=80 m=20 |
|---|---|---|---|---|---|---|
| FAS (NP) | 0.0011 | 0.0005 | 0.0006 | 0.0007 | 0.0009 | 0.0043 |
| RFAS (NP) | 0.0461 | 0.0426 | 0.0574 | 0.0611 | 0.0809 | 0.4490 |
| GLS (NP) | 0.7934 | 0.6459 | 1.1393 | 0.7797 | 1.0405 | 6.2788 |
| SA (NP) | 1.5405 | 1.3268 | 2.3709 | 1.6087 | 2.2009 | 12.1459 |
| FAS (P) | 0.0023 | 0.0014 | 0.0013 | 0.0018 | 0.0012 | 0.0101 |
| RFAS (P) | 0.0937 | 0.1251 | 0.1172 | 0.1604 | 0.1041 | 0.9499 |
| GLS (P) | 1.3276 | 1.1175 | 2.4538 | 1.7933 | 1.1995 | 16.7991 |
| SA (P) | 2.7548 | 2.7818 | 5.0949 | 3.8514 | 2.3212 | 33.6078 |

5. Implementation of Scheduling Technique

Effects on the demand profile were examined by simulating the preemptive and non-preemptive SA algorithms for the case of 80 EVs and 20 charging stations. Electrical demand data and charger availability from the University of Louisville was utilized. The performance of these algorithms are compared to the base case of uncontrolled charging activity. Figure 47 shows the results of applying the SA scheduling algorithms. As a peak is reached in the demand profile of the base load, charging stations are disabled to prevent EV charging loads from further driving the peak higher resulting in lower electrical demand costs. The differing behaviors of the preemptive and non-preemptive algorithms can be seen in Figure 47 as well. The non-preemptive variant does not schedule charging jobs if they overlap with scheduled down times. Therefore, the added demand from EV charging activity trails off as the peak nears. Conversely, the preemptive algorithm continues charging activity until charging stations must be disabled. This results in a sharp drop in electrical demand for the following 15 minute demand interval. As expected, the makespans of both algorithms are longer than the base case without control. Additionally, since the preemptive scheduling algorithm allows charging activity to continue until stations must be disabled, its total makespan is slightly less than the non-preemptive variant. Finally, Figure 47 also indicates the number of machines, among a total of 20, that are allowed to operate by the PMCS at each time interval. There are some periods where all charging activity is halted and others where this activity is limited.

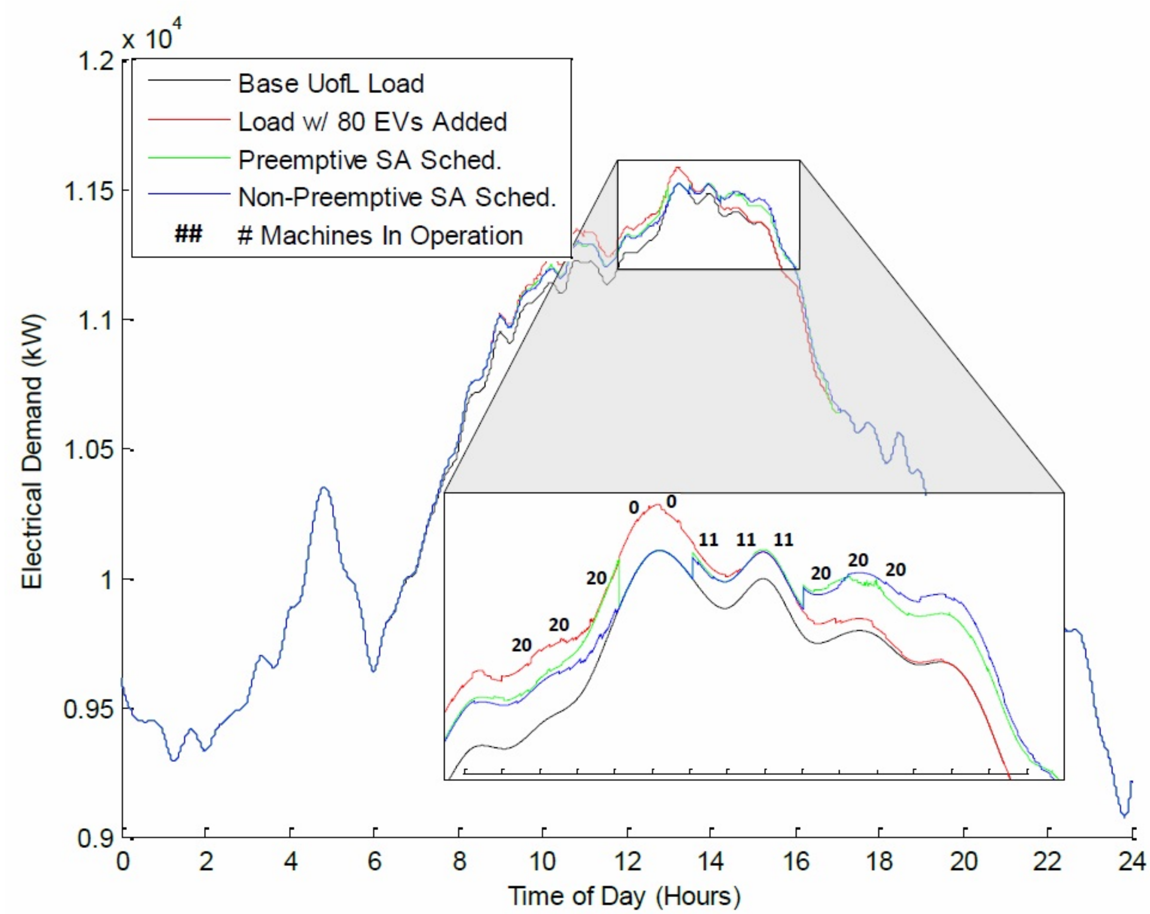



FIGURE 47: Simulation results for 80 electric vehicles on University of Louisville campus.

Table 12 summarizes the impact of the PMCS and scheduling algorithms on the added cost of charging activity and the total makespan of the charging process. Electrical cost increases were calculated using the rate structures outlined in section II.D. There is a clear tradeoff between added electrical cost and total makespan when controlling EV charging activity. Both scheduling algorithms simulated resulted in no demand charge increase over the base electrical load, however the total makespan for each case was slightly longer than the base case. Table 12 assumes no error in the

TABLE 12

Comparison of charging cost increases and total makespan for SA algorithms.

| 80 Electric Vehicles 20 Charging Stations | C&I Energy Cost Increase | C&I Demand Cost Increase | C&I Total Cost Increase | Makespan (Hours) |
|---|---|---|---|---|
| Uncontrolled Charging | $439.30 | $4,010.80 | $4,450.10 | 8.999 |
| Preemptive SA Sched. | $439.30 | $0.00 | $439.30 | 11.801 |
| Non-preemptive SA Sched. | $439.30 | $0.00 | $439.30 | 12.947 |

electrical demand forecast provided.

The forecasting algorithms described in this section are off-line algorithms. They assume that the arrival times and processing times of all jobs are known before the schedule is formulated. This is not the case for the PMCS though since EVs may arrive at varying times each day and also may have varying states of charge from day-to-day depending on driver behaviors and driving patterns. The off-line scheduling approach is beneficial for applications where the schedule is required for the entire day and is only calculated once. However when implemented into the PMCS, the schedule is re-formulated every 15 minutes. The Matlab m-files for the preemptive and non-preemptive SA scheduling algorithms can be found in Appendices III and IV. The combined control m-file in Appendix II includes a placeholder for the preemptive SA scheduling algorithm which was chosen for implementation into the PMCS due to its shorter makespan. Other scheduling algorithms including the FAS, RFAS, and GLS algorithms are not included in the Appendices.

## E. Control of EV Charging Activity

The final module of the PMCS, module #4, provides control of charging activity through direct communication links between the control system and the EVSE. This module takes the output of the forecasting and scheduling modules and implements the control strategy among the EVSE installed. A number of control strategies were studied including centralized and distributed control. Centralized control utilizes a central controller unit that communicates with each system component directly. Typically, nodes in a centralized control system are "dumb" and do not provide any control themselves. Instead, they require the central controller to make all decisions. A distributed control system does not use a centralized controller. In this type of control system, each node makes control decisions while communicating with nearby neighbors to make the system aware of its behavior.

Centralized and distributed control systems each have a number of benefits and disadvantages. For example, centralized controllers are much more simple to implement, however they require higher processing power at the central node. Distributed controllers create network topologies that can be changed without the need to take large portions of the control system down. Figure 48 shows the relation between centralized, de-centralized, and distributed control strategies.

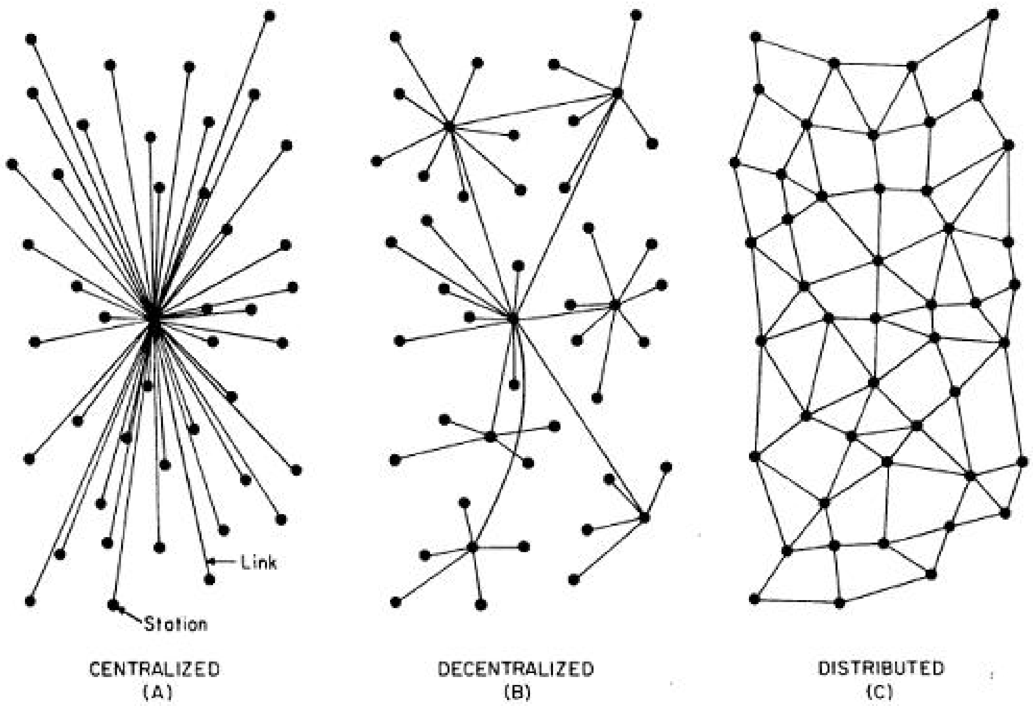



FIGURE 48: Types of control strategies / topologies.

Control topologies should not be confused with communication topologies. Control systems can use a multitude of communication network topologies but still operate as a centralized or distributed controller. More information regarding the communication topology and strategies is provided in the following chapter. The PMCS uses a centralized approach for control. Due to the relatively small size of the PMCS network and the computational complexity of the forecasting and scheduling algorithms, the centralized control system provided a better approach. A hybrid approach was considered, where the forecasting and scheduling would occur on a central node, but each EVSE node would provide its own control of charging activity. This would require additional computing power at each EVSE node, since a typical EVSE functions as an electrical switch and has little processing capability. In order to avoid the added cost of adding the required computing power, the decision was made to implement the entire control system at the central node.

The control module of the PMCS operates by keeping track of how many vehicles are connected and charging at any one point in time. When the forecast or schedule is produced from the other modules of the PMCS, the control module then determines which stations to turn off or on for the next 15 minute demand interval. Serial commands are then sent out to each of the EVSE affected by the control decision. Future capabilities could be added to enable security measures if deemed necessary. The control module has the capability to keep track of users and authenticate who is allowed to use the EVSE during certain times throughout the day. Currently, the EVSE are configured to allow any user at any time given that they have a charging identification badge/card. The EVSE requires the user to wave their identification card near the RFID scanner installed on each charging station before a charging process can commence. This provides adequate security to prevent unauthorized use, but as the size of the system expands or new EVSE locations are installed, the PMCS provides the capability to control users and access to charging capability.

The GE DuraStation EVSE [44] installed on the University of Louisville's Belknap campus provide the capability to be connected to a centralized control system. Typically this feature is disabled because it was developed by the manufacturer (General Electric) for future expansion of new product lines. General Electric, who is aware of the ongoing research involving their EVSE, graciously provided the proper firmware to enable this capability. With the installation of the new firmware, each

EVSE can be individually addressed and controlled via a series of serial commands. These commands can be used to gather information such as charging status, power consumption, and other health related information from each charging station. Additionally, the serial commands allow the user to specify charging rates, enable and disable charging, and authorize or de-authorize a charging station user. The structure of the serial commands can be found in Figure 49. Additionally, Table 13 provides a list of the various commands enabled with the new firmware. In Table 13, XX represents the serial address of each EVSE. These addresses are specified in the following chapter in the discussion regarding the network topology.

| STX | Address | Packet Length | Message Type | Data | Check-Sum | ETX |
|---|---|---|---|---|---|---|
| 1 byte | 1 byte | 2 byte | 1 byte | N byte | 2 bytes | 1 byte |

FIGURE 49: Message packet structure for GE DuraStation EVSE [81].

The centralized control module of the PMCS works directly with the GE DuraStation to control charging activity. The EVSE itself does not make any control decisions regarding charging. A program was written in Matlab [67] to interface with the new firmware on the EVSE. This program can be found in Appendix V. The program included in Appendix V assumes a fixed EVSE serial address and simply lists the various serial commands available. The control module uses these commands along with the proper address of the EVSE to send out the correct command to satisfy the PMCS forecast and schedule.

TABLE 13

Summary of serial commands utilized by GE EVSE [81].

| **Command Type** | **Serial String (Hex)** | **Command / Request** |
|---|---|---|
| Heartbeat | 02 XX 08 00 15 XX 1D 13 | Request |
| Get Status | 02 XX 08 00 31 XX 39 13 | Request |
| Measure Power | 02 XX 08 00 38 XX 40 13 | Request |
| Charge Enable | 02 XX 08 00 10 XX 18 13 | Command |
| Charge Auth. | 02 XX 08 00 57 XX 5F 13 | Command |
| Charge Disable | 02 XX 08 00 11 XX 19 13 | Command |

## F. User Interface for System Monitoring and Control

One of the research objectives is to develop a user interface for monitoring and supervisory control of the PMCS. The primary function of the user interface is to provide a summary of the PMCS performance. It also provides information regarding EVSE availability, and notes when a number of EVSE must be disabled due to an approaching electrical demand peak. Additionally, the user interface provides a summary of total energy consumed by EV charging activity. Finally, the last goal of the user interface is to provide supervisory control of the charging process. System administrators can use the interface to temporarily disable charging or override charging outages in cases where electrical demand and cost is not a factor. The user interface that has been developed for the PMCS was developed using Matlab software since the majority of the algorithms and control strategies were also implemented using Matlab. The database containing the data collected and forecasted by the PMCS is also managed by Matlab.

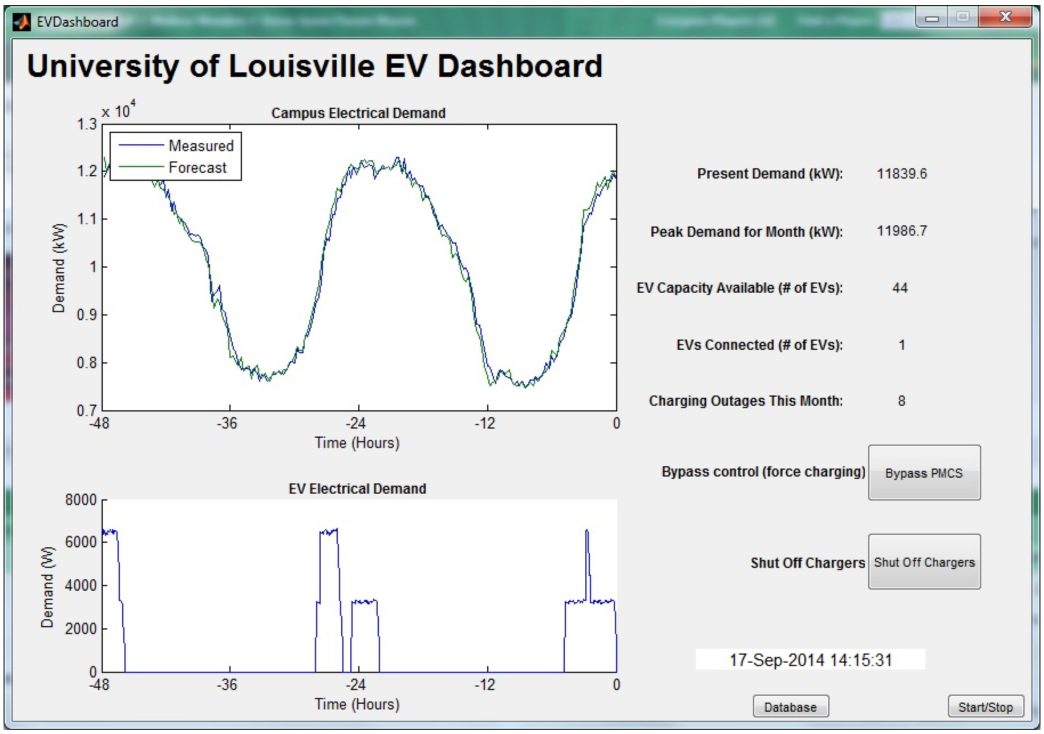



FIGURE 50: User interface developed in Matlab for PMCS.

The user interface shown in Figure 50 continually updates to show the most current readings. The plots show a sliding window of the previous 48 hours of electrical demand. The top plot shows the actual and forecasted electrical demand for the entire campus. These values are utilized in determining the total number of chargers that can be active for the ensuing 15 minute demand interval. The bottom plot shows the aggregate EV load measured by the charging stations. Controls are provided to override charging outages and force chargers to remain active or to disable charging if desired. Finally, a link is provided to the historical database that stores approximately 3 months of data. Future revisions of the user interface shown in Figure 50 should include data collected from the EV interface including state of charge for connected vehicles.

# CHAPTER V
# NETWORK TOPOLOGY AND COMMUNICATION STRATEGY

Network topology, or the structure through which individual network nodes communicate with one another, is an important aspect to the design of a control system. In the case of the PMCS described in this dissertation, the network topology is determined by the location of the EVSE in relation to the location of the PMCS controller unit. Network topologies can also vary based on the technology or medium chosen to implement the communication infrastructure. Wired communication technologies tend to be configured in star or tree-based topologies. Wireless communication technologies, on the other hand, allow for additional topologies such as mesh or grid type networks. This section will describe the various networking topologies and transmission mediums or technologies considered for implementation of the PMCS. The communication technology and topology chosen will be described and details will be provided to define how the network is configured for the EV charging testbed on the University of Louisville Belknap campus.

## A. Discussion of Network Topologies

Network topologies can be divided into two main subcategories, physical and logical network topologies. Physical network topologies are determined by the medium and network equipment used to interconnect nodes. Physical network topologies is the most common category. Logical network topologies, on the other hand, utilize higher level transmission protocols to emulate a given network topology regardless of the physical interconnection between network nodes. Logical network topologies tend to operate slower, depending on the logical topology implemented, due to the protocol overhead required to deliver data packets. Therefore, several physical network topologies were considered for implementation of the PMCS. Figure 51 represents the most common network topologies implemented in computer networks. The earliest computer networks utilized either bus or ring-based architectures. In these topologies, only a single node could communicate at a time in order to prevent collisions of data packets. This led to the development of tree and star-based network architectures. These topologies greatly improved network throughput but also limited the size of the network to the lengths of wiring required to interconnect nodes to a central location. Newer sensor-based networks utilize mesh and fully-connected grid based topologies. These provide multiple paths between any two selected nodes. Network throughput can be improved, and the addition or removal of nodes is much easier. Partially connected mesh networks make it possible to take advantage of some of the redundancy that is provided by a physical fully connected mesh topology without the expense and complexity required for a connection between every node in the network.

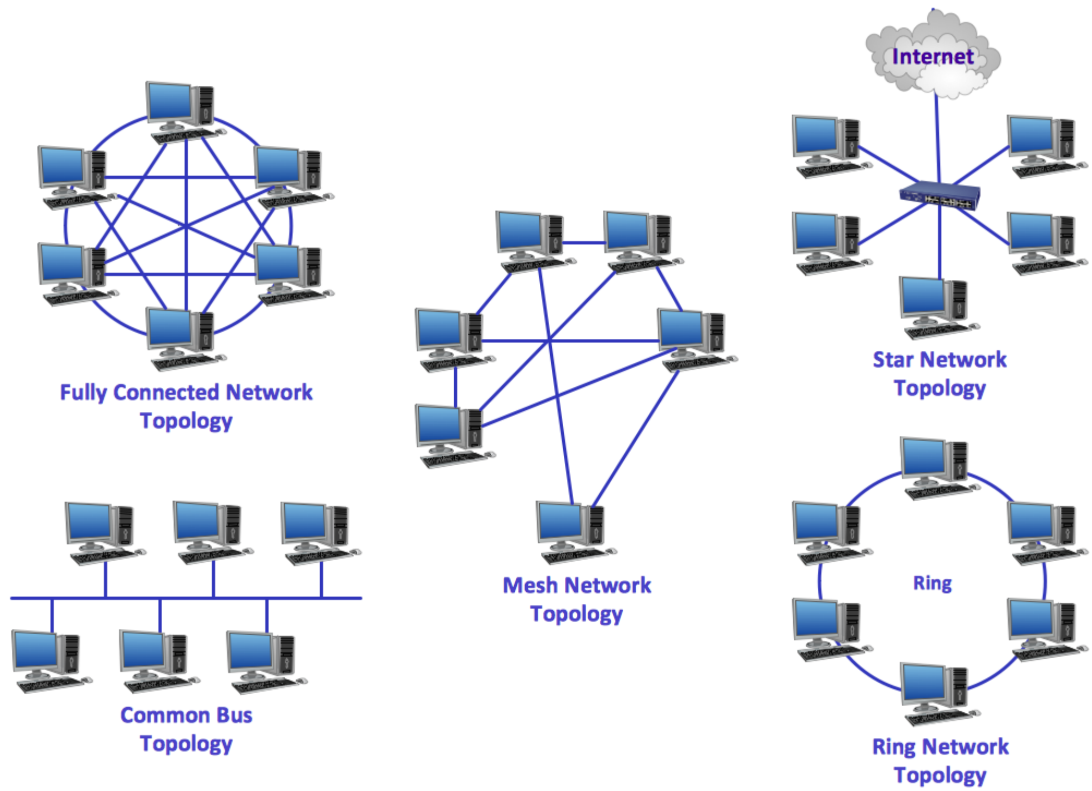



FIGURE 51: Various physical network topologies possible for interconnecting network nodes [82].

When implementing the PMCS into the EV charging testbed at the University of Louisville, a hybrid approach to connecting devices was taken due to the location and distance between nodes within the PMCS network. Ideally, a star-based approach would be the most beneficial to improve throughput and network performance, but this can become costly due to the distances between charging stations. Instead a hybrid combination of a star and mesh-based network topology was chosen. Logically, the PMCS controller communicates directly to a given node therefore simulating a star-based topology. Physically, the communication infrastructure consists of a variety of directly wired and wireless connections. EVSE nearby the PMCS controller are either directly wired back to the PMCS, or form a direct point-to-point wireless network connection. Other EVSE are connected through a mesh network and data packets traverse a few nodes before reaching the PMCS controller. EVSE and vehicles are interconnected to other network nodes through a mesh-based topology, but each node is individually addressed to assist in the communication process. More information regarding addressing is provided in a later section of this chapter. The following sections will outline the wired and wireless networking technologies considered and utilized for implementation of the PMCS.

## B. Wired Networking Technologies

The simplest form and most secure method of communicating between two devices is over a wired connection. Hard wired network connections provide greater security that wireless links because outside intruders must physically break or attach to the wired connection to gain access to the data transmitted. These connections are an integral part of the PMCS design. The majority of computer networks in service today utilize wired ethernet connections between network nodes. Wired ethernet was originally considered for connecting each of the EVSE installed for the University of Louisville testbed. However after quick research, it was decided that wired ethernet would not be acceptable for a number of reasons. The primary reason is that there are added costs to connecting each EVSE via ethernet to the University's production network. The increased cost is due to the remote locations of the chargers and the need to install new network infrastructure to support such devices on the network.

The University, along with numerous other commercial networks, typically charge a monthly service fee for each network drop as well which would add to the operating costs of the charging infrastructure. The main goal of the PMCS is to minimize the energy and communication cost impact of the EVSE, so a large scale deployment becomes economically feasible. Additionally, the University faces a new network security risk as intruders now have a somewhat un-secure method of attaching to the production network. Finally, control of the GE DuraStation charging stations installed as part of the EV charging pilot project cannot be achieved through the ethernet port on each EVSE. This is a limitation of the design and engineers at General Electric, the EVSE manufacturer, have noted that other EVSE manufacturers do not allow control of charging infrastructure through the ethernet port. Due to these reasons, wired ethernet was not considered as an option for the PMCS networking technology.

The primary wired networking technology utilized in the PMCS design is RS-232 serial communications. It is very common for EVSE to have a RS-232 serial port installed for allowing simple communication with the controller located inside the charging station. The PMCS does not require extremely fast data throughput, therefore simple serial communications are the easiest to implement. Logical point-to-point serial communication links are formed between the network nodes of the PMCS. RS-232 typically has a range limit of 30 to 50 feet due to capacitance and impedance losses in the signal wires. Therefore, wired RS-232 is only utilized within the EVSE between the controller and the wireless ZigBee translational bridge. Figure 52 shows the controller board installed in the GE DuraStation. The serial communication port is a DB9 DTE connector. It is represented by J6 in Figure 52.

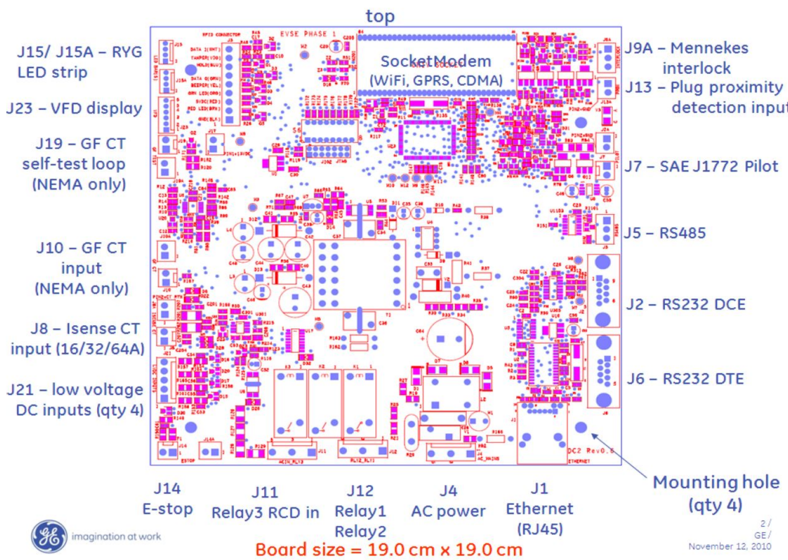



FIGURE 52: EVSE controller board installed in GE DuraStation [44].

## C. Wireless Networking Technologies

Due to the remote locations of the EV charging infrastructure in typical installations, and the distance between EV chargers, wired network connections are not always the most cost effective method of communications. Therefore, a wireless communication infrastructure is preferred. Several options were considered including wireless ethernet, Bluetooth, and ZigBee. There are a number of advantages and disadvantages to each of these options. This section will compare and contrast each of the wireless technologies considered and will provide evidence supporting the technology chosen. Figure 53 provides a summary of the various wireless technologies considered. Note that this summary also includes Ultra-WideBand (UWB) communications, however this technology was not considered because of its similarities to the much more common Bluetooth and ZigBee technologies.

| Standard | Bluetooth | UWB | ZigBee | Wi-Fi |
|---|---|---|---|---|
| IEEE spec. | 802.15.1 | 802.15.3a * | 802.15.4 | 802.11a/b/g |
| Frequency band | 2.4 GHz | 3.1-10.6 GHz | 868/915 MHz; 2.4 GHz | 2.4 GHz; 5 GHz |
| Max signal rate | 1 Mb/s | 110 Mb/s | 250 Kb/s | 54 Mb/s |
| Nominal range | 10 m | 10 m | 10 - 100 m | 100 m |
| Nominal TX power | 0 - 10 dBm | -41.3 dBm/MHz | (-25) - 0 dBm | 15 - 20 dBm |
| Number of RF channels | 79 | (1-15) | 1/10; 16 | 14 (2.4 GHz) |
| Channel bandwidth | 1 MHz | 500 MHz - 7.5 GHz | 0.3/0.6 MHz; 2 MHz | 22 MHz |
| Modulation type | GFSK | BPSK, QPSK | BPSK (+ ASK), O-QPSK | BPSK, QPSK COFDM, CCK, M-QAM |
| Spreading | FHSS | DS-UWB, MB-OFDM | DSSS | DSSS, CCK, OFDM |
| Coexistence mechanism | Adaptive freq. hopping | Adaptive freq. hopping | Dynamic freq. selection | Dynamic freq. selection, transmit power control (802.11h) |
| Basic cell | Piconet | Piconet | Star | BSS |
| Extension of the basic cell | Scatternet | Peer-to-peer | Cluster tree, Mesh | ESS |
| Max number of cell nodes | 8 | 8 | > 65000 | 2007 |
| Encryption | E0 stream cipher | AES block cipher (CTR, counter mode) | AES block cipher (CTR, counter mode) | RC4 stream cipher (WEP), AES block cipher |
| Authentication | Shared secret | CBC-MAC (CCM) | CBC-MAC (ext. of CCM) | WPA2 (802.11i) |
| Data protection | 16-bit CRC | 32-bit CRC | 16-bit CRC | 32-bit CRC |

* Unapproved draft.
• Acronyms: ASK (amplitude shift keying), GFSK (Gaussian frequency SK), BPSK/QPSK (binary/quardrature phase SK), O-QPSK (offset-QPSK), OFDM (orthogonal frequency division multiplexing), COFDM (coded OFDM), MB-OFDM (multiband OFDM), M-QAM (M-ary quadrature amplitude modulation), CCK (complementary code keying), FHSS/DSSS (frequency hopping/direct sequence spread spectrum), BSS/ESS (basic/extended service set), AES (advanced encryption standard), WEP (wired equivalent privacy), WPA (Wi-Fi protected access), CBC-MAC (cipher block chaining message authentication code), CCM (CTR with CBC-MAC), CRC (cyclic redundancy check).

FIGURE 53: Comparison of wireless networking technologies [83].

### 1. Bluetooth

Bluetooth, also known as IEEE 802.15.1, is a short range, low power wire-replacement communication technology. Depending on the class of the Bluetooth transceiver, the transmission range can vary from 1 meter to 100 meters. Bluetooth is typically considered a Personal Area Network (PAN) due to its short range communication capabilities. A collection of Bluetooth devices within wireless transmission range of the master controller is considered a piconet. A collection of overlapping piconets can be interconnected to form a larger scatternet. Figure 54 demonstrates the relationship between master / slave nodes, piconets, and scatternets.

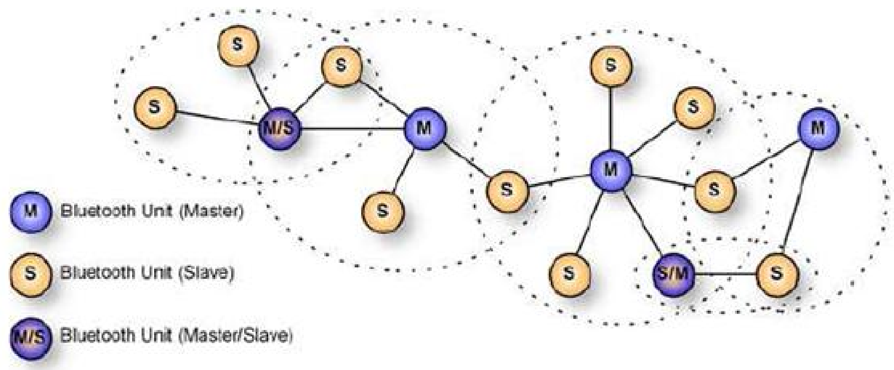



FIGURE 54: Scatternet of Bluetooth devices [84].

Bluetooth provides an enticing option for the networking requirements of the PMCS. Bluetooth is a common networking technology and there are several translational bridges available that are compatible with RS-232 serial communications. Bluetooth can use both point to point and mesh networking topologies. Bluetooth is an older technology that was originally introduced by Ericsson in 1994. The technology standard has undergone several revisions, including the latest 4.0 standard that introduces a low energy variant of the technology. Bluetooth Low Energy (Bluetooth LE) improves on the traditional Bluetooth technology by providing similar range with a fraction of the power consumption. The one downside to most Bluetooth and

Bluetooth LE devices is that the antenna is typically on-chip or ceramic based since most Bluetooth networks do not have extended ranges. Unfortunately, it is desirable to locate the wireless communication bridge inside the EVSE enclosure for security purposes. Most EVSE enclosures are metallic which poses a problem with wireless communications. Even though Bluetooth would provide a great communication medium due to its built-in security features such as a stream cipher for encryption and a shared secret password for authentication, other wireless infrastructures were considered.

2. ZigBee

ZigBee, or IEEE 802.15.4, is a low-cost, low-power wireless mesh based communication technology developed specifically for sensor and control networks that do not require high data rates. ZigBee is a common communication technology utilized in smart grid applications for that reason. Most smart grid applications utilize ZigBee because of its simplicity and ease of use. Unlike Bluetooth which operates strictly in the 2.4 GHz band, ZigBee can operate in 3 different bands including 2.4 GHz, 900 MHz, and 868 MHz [85]. The lower frequency variants have increased range between nodes. Additionally, ZigBee can support up to 65,000 nodes per network as opposed to Bluetooth that can only support up to 8 nodes per piconet due to its 3-bit addressing. Comparatively, ZigBee has a lower power consumption than Bluetooth as well. However this is not a factor with the introduction of Bluetooth LE as these devices use a similar amount of power as ZigBee devices [83].

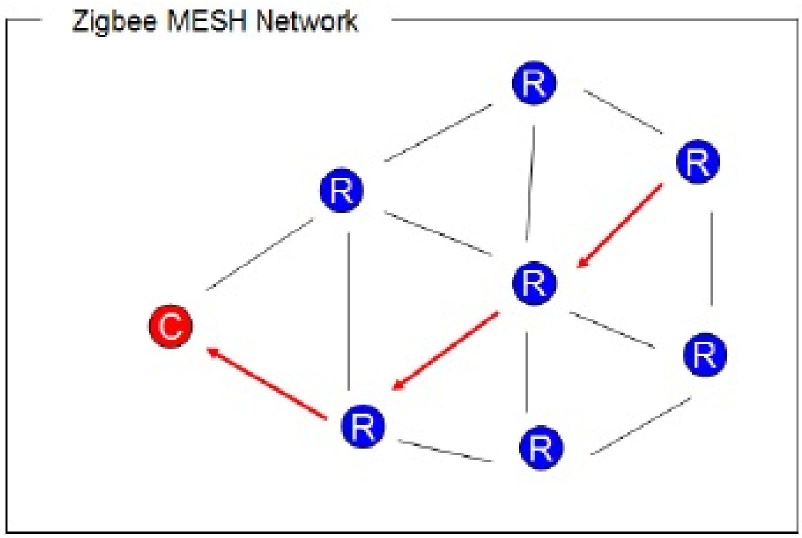



FIGURE 55: ZigBee mesh network [86].

Figure 55 represents a typical ZigBee mesh network. ZigBee nodes can be one of two types: a Coordinator or a Router. Every ZigBee network must have 1 coordinator device that can manage addressing and control the addition or removal of network nodes. Any node can send or receive data or act as a router and route data packets through the node. Any node can be added or removed from the network at any point as long as the coordinator is powered on and active. If the coordinator node is removed or powered down, the network will still function as normal, however nodes cannot be added or removed. Each node can be configured with a static PAN ID, or network identifier, or it can be set to automatically attach to the nearest ZigBee network. In addition to the 16-bit PAN ID, each node must be configured with its own 16-bit address.

ZigBee also has several benefits related to data and network security. Nodes can be configured so that PAN identification is kept hidden. This will help prevent unauthorized nodes from joining. Additionally, ZigBee provides a block cipher for encryption of transmitted data and utilizes a CBC-MAC (cipher block chaining message authentication code) for authentication of messages. These security measures are similar to wireless ethernet protocols.

3. Wi-Fi (Wireless Ethernet)

Finally, wireless Ethernet is also an option for the communication infrastructure of the PMCS. Wireless Ethernet networks are prolific and translational bridges are plentiful as well. Wireless Ethernet, or Wi-Fi, typically operates on the 2.4 and 5 GHz spectrums. There are several variants of Wi-Fi including: 802.11a, 802.11b, 802.11g, 802.11n, and 802.11ac just to name a few. These provide faster communication speeds that range from 10 Mbps up to over 100 Mbps. Wi-Fi networks tend to operate over larger areas as well. Whereas Bluetooth and ZigBee networks were typically limited to shorter transmission ranges, such as 10 to 50 meters, Wi-Fi can extend beyond 100 meters.

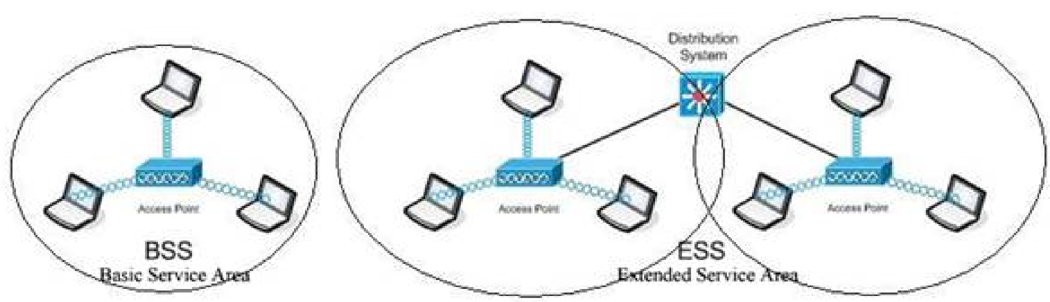



FIGURE 56: Typical Wi-Fi network showing relationship between BSS and ESS [87].

The basic building block of a Wi-Fi network is the Basic Service Set (BSS).

This encompasses a single access point and several nodes that connect to that access point. Similar to Bluetooth, a BSS can be connected to another BSS through a router to form an Extender Service Set (ESS). This relationship is depicted in Figure 56. With an ESS, nodes can traverse from one BSS to another without dropping connection or requiring a node to re-join the network.

As stated previously, Wi-Fi is prolific and almost all portable devices today are Wi-Fi compatible. This poses a problem in that it is desired for the PMCS to be a stand-alone network for security purposes. With Wi-Fi networks at commercial locations such as college campuses and shopping centers, Wi-Fi would give the option to add EVSE and vehicle nodes directly to a production network. However most network administrators frown on this for fears of security risks that are added to the production network. Also, adding Wi-Fi capabilities in remote locations such as parking garages and parking lots may not be feasible for some.

### 4. Discussion of Wireless Technology Chosen

Cost is an extremely important factor when choosing a wireless technology for practical implementation of the PMCS. As previously stated, wired ethernet typically has a monthly service fee associated with it for large commercial networks. For example, at the University of Louisville an ethernet drop has an initial cost of approximately \$100 and also has a recurring monthly service charge of \$10. This cost is not scalable for large deployments of EV charging infrastructure. Comparatively Wi-Fi has an initial cost of around \$50 with no recurring monthly service charge. ZigBee has an initial cost of \$25 per node and Bluetooth has an initial cost of \$20 to \$30 per node. Neither ZigBee nor Bluetooth have recurring monthly service charges. Of the various wireless technologies listed here, ZigBee has the lowest relative cost, especially when wireless range is considered. ZigBee is the only networking technology of the four considered that has a range longer than 300ft. The ZigBee modules utilized for implementation have an effective range of 1600 meters with direct line-of-sight.

The PMCS outlined in this dissertation utilizes a number of networking technologies to interconnect nodes to the controller while attempting to minimize networking costs. Wi-Fi is utilized as the primary connection to the master controller unit from the production network. The master controller uses this connection for communication with internet connected sensors and databases which are accessed by the data collection module of the PMCS. The Wi-Fi link also provides a gateway for the user interface that is responsible for monitoring and management of the PMCS. For security purposes, the PMCS does not utilize Wi-Fi for connecting EVSE nodes of vehicle nodes to the PMCS.


FIGURE 57: DTK RS-232 to ZigBee translational bridge [86].

Instead, the PMCS communicates to EVSE and vehicle nodes through a wireless serial interface. DB-9 RS-232 wired interfaces are utilized within each EVSE to communicate with the EVSE controller board which provides access to power monitoring, and control of the electrical contactor. Due to the physical limitations of the RS-232 protocol and hardware, wireless ZigBee translational bridges are used at each EVSE to convert the RS-232 connection to a wireless ZigBee connection. ZigBee was chosen due to its low cost and because it is commonly used in smart grid applications.

The ZigBee bridges shown in Figure 57 act as nodes on a mesh network that is formed between the various devices connected. Since each EVSE has its own serial address, a broadcast command sent from the PMCS controller will traverse the entire ZigBee network to every node, but only the node with the corresponding address will respond with the desired information. Additionally, vehicle nodes are connected to the ZigBee mesh network through ZigBee to OBDII adapters. Figure 58 shows the

ZigBee to OBDII adapters utilized with the PMCS. These OBDII adapters allow the PMCS to collect state of charge data from connected EVs for use in the prioritization algorithm. Also shown in Figure 58 is a USB node that can be used to connect directly to the vehicle though a laptop PC if the EV owner prefers to monitor data without the use of the PMCS.

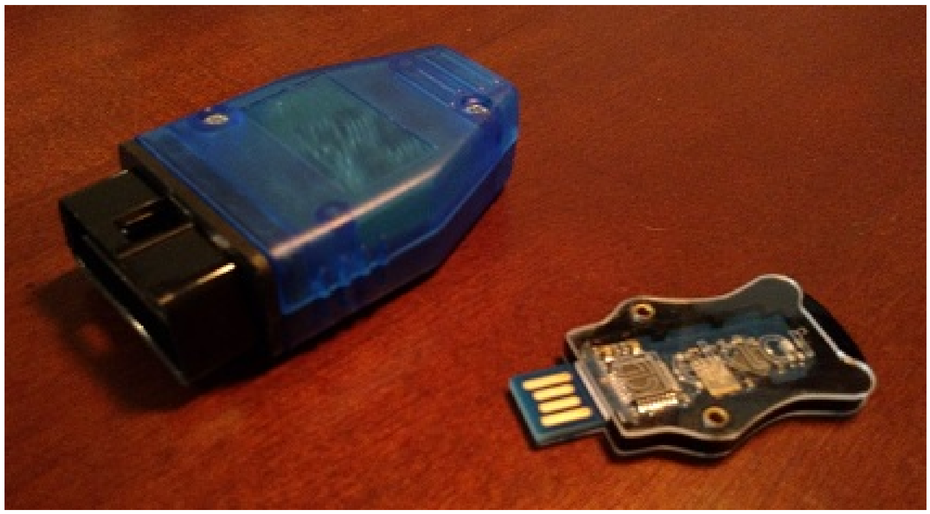


FIGURE 58: OBDII to ZigBee adapter for vehicle nodes.

Due to the multitude of communication technologies used in the PMCS, addressing is a very important aspect of the design to ensure reliable delivery of data and control of charging. By default, the PAN ID for the ZigBee wireless network is set to 0x199B on the ZigBee to RS-232 bridge devices. This was changed to 0x1000 to help deter the possibility of someone connecting to the PMCS network inadvertently. 16 bit ZigBee addresses are assigned at random by the coordinator as these appear transparent to the overall function of the wireless network. The 16 bit ZigBee addresses are only used by the routers and coordinator to pass data throughout the mesh network. 8 bit serial addresses are configured on every EVSE controller board as shown in Figure 59. When commands are sent from the PMCS controller, these serial addresses are used to send commands to a given network node. The command is flooded across the mesh network, but only the station with the designates serial address will respond to the command. When the EVSE responds, the data is sent directly to the PMCS controller master node.

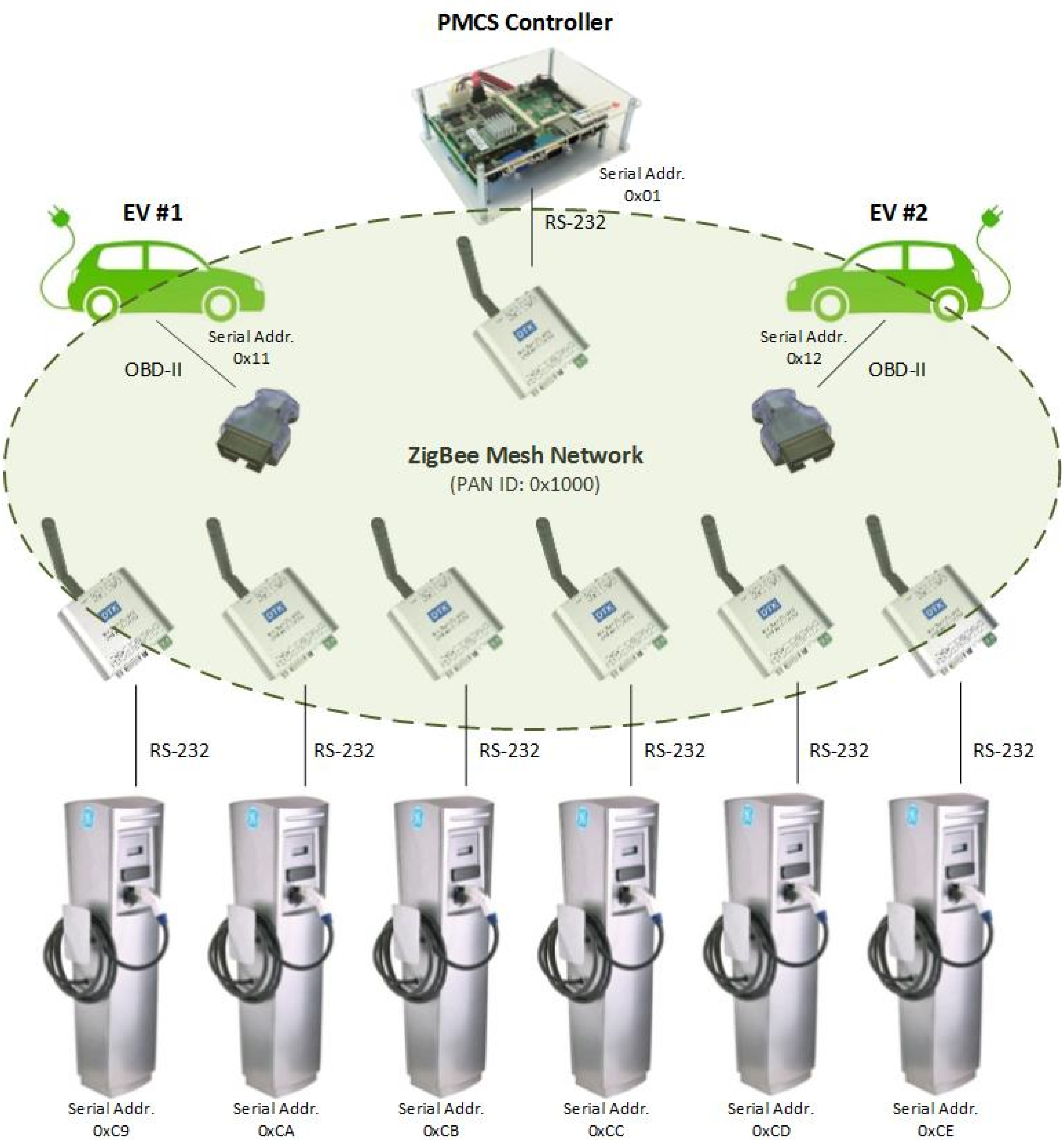



FIGURE 59: ZigBee network showing serial addressing.

## D. Discussion of Cyber Security Risks

With any network, there are a number of cyber security risks that must be addressed. This section will address the security risks associated with the PMCS and will describe how these risks are avoided or prevented. In the case of the PMCS it is important to not only protect the data collected, but also the user experience of the control system. It is also important to ensure that security breaches to commercial and industrial networks are not facilitated by the PMCS since it does connect to these networks for data collection purposes. The PMCS collects valuable data such as energy usage profiles, and vehicle arrival patterns. Protecting this data from intruders is important to ensure the safety and security of patrons utilizing the EVSE infrastructure and the electric ratepayer. Furthermore, since the PMCS provides control of EV charging activity, it is possible for an attacker to take control and disable or enable charging activity during periods that would result in incomplete charge levels for EVs or increases in peak electrical demand. Therefore preventing such attacks and security breaches is important for the PMCS and must be considered.

The communication technologies utilized by the PMCS were chosen in an attempt to limit the possibility of a cyber security attack. Default protection levels provided by the communication technologies themselves were considered adequate for the PMCS. WPA2 enterprise Wi-Fi security for communication with the production network is utilized to prevent security breaches between the PMCS and the wireless

Ethernet production network. Counter mode AES block ciphers are used to encrypt data transmitted over the ZigBee mesh network, along with CBC-MAC authentication protocols, and a 16-bit Cyclic Redundancy Check (CRC) for data integrity. Wired communication technologies used are located within the EVSE enclosure to prevent unauthorized access. No additional cyber security measures were taken due to the robustness of the existing measures within the communication technologies and mediums utilized.

# CHAPTER VI
# RESULTS, CONCLUSIONS AND FUTURE WORK

At the start of this research, a problem statement was formulated noting that EV charging is not scalable due to resultant increases in electricity demand peaks and associated communication costs, which will significantly increase the total cost of charging for commercial or industrial time-of-day electric ratepayers. The hypothesis drafted states that an accurate forecast of electricity demand with minimal error, along with a prioritization algorithm and control system, will significantly minimize the total cost of EV charging. This hypothesis has held true for the PMCS detailed in this work.

The novel power monitoring and control system developed in Chapter IV has been simulated and demonstrated with positive results. Significant reductions in electrical cost can be realized by intelligently scheduling charging activity around demand peaks. In addition to the significant simulation results, the power monitoring and control system has also been implemented in an electric vehicle charging testbed at the University of Louisville for further testing. Through implementation of this system, meaningful data has been collected to supplement proof of the benefits of such a system for EV charging hubs. Simulation data cannot predict abnormalities that may happen in a real life scenario, so the installation of the system is critical for testing purposes. All objectives outlined in chapter I have been achieved.

This chapter will outline the testing and simulation results as well as display results that have been collected after implementing the power monitoring and control system into the EV charging testbed. Conclusions will be drawn regarding the operation of the control system and suggestions will be made for future studies to be conducted. Significant benefits to the electric utility, the C&I electric ratepayer, and the EV owner are achieved by taking advantage of the relatively short charge cycles of typical PHEVs. Charging availability is maximized throughout the day and is only disabled when demand peaks occur for the billing period. Consequently, by avoiding charging when peaks occur in electrical demand, the cost of electricity per unit is significantly reduced.

## A. Key Accomplishments

The following list is a summary of the key accomplishments achieved throughout the design, simulation and testing, and implementation of the power monitoring and control system.

- Increases in electrical demand due to EV charging activity are limited to the error in the forecasting algorithm.
- The total cost of EV charging activity in C&I environments was reduced by nearly 90%.
- An accurate forecasting algorithm was developed limiting mean absolute percent error to +/- 0.02% in a best-case scenario. This results in a mean absolute error of 3 to 10 kVA.

- A prioritization algorithm was implemented to create a fair charging experience for all electric vehicles connected and charging.
- A simulated annealing scheduling algorithm was developed that minimizes total processing time to an optimal result for cases where number of EVs is much greater that total EVSE availability. The optimal result was determined by solving a mixed integer programming model.
- The final power monitoring and control system design was implemented into EV charging testbed at the University of Louisville.
- A database was formed containing several months of test data.
- Operation of the PMCS was verified to limit demand peaks and minimize additional cost of charging activity.
- Communication / IT costs minimized by avoiding wired and wireless ethernet.
- Adequate cyber security measures were implemented to protect data and prevent tampering with the control system.
- Over 5000 lines of code were written in Matlab software in order to simulate and implement various algorithms required by PMCS.

## B. Results of Study

The power monitoring and control system for EV charging activity has provided optimistic and promising results from both simulations ran, and practical implementation of the system in the University of Louisville EV charging testbed. This section will discuss these results and aims to prove the value of such a control system. Simulations and implementable versions of the various algorithms were written in the Matlab software suite [67].

The PMCS was implemented at the University of Louisville utilizing a collection of 6 level II GE DuraStation [44] EV chargers and test results were collected over the course of this research work. A new EVSE firmware was developed by GE engineers to allow communication with and addressing of each charging station. Additionally, one of the GE DuraStation charging stations was modified by the addition of a PC to run the PMCS algorithms. The PC runs the forecasting and scheduling algorithms every 15 minutes and sends control signals to the 6 charging stations as required. Figure 60 shows the modifications made to the GE DuraStation to allow implementation of the PMCS algorithms. The PC was mounted inside the enclosure and Wi-Fi antennas were added to provide access to the internet. If Figure 60, the PC can be seen on the right behind a protective plastic shield, and is circled for clarity.

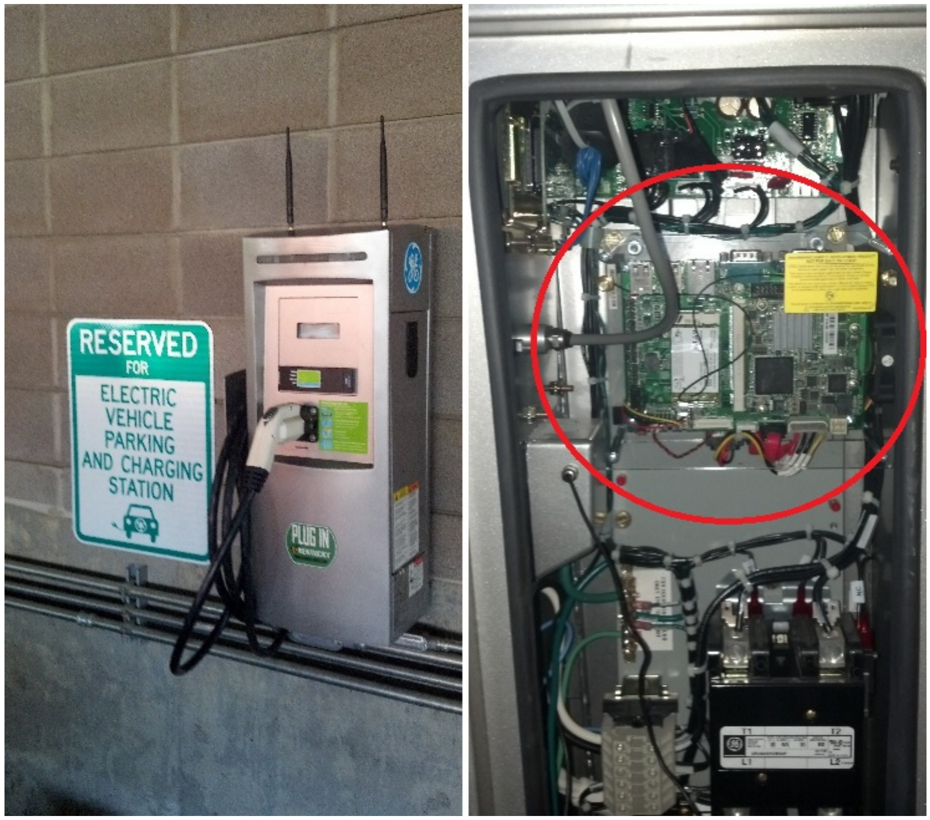



FIGURE 60: Modifications made to the GE DuraStation to allow implementation of the PMCS.

The resulting reduction in electric cost is dependent on a highly accurate electrical demand forecast. A number of forecasting algorithms were studied and compared to determine the best performance. Table 8 in Chapter IV shows a quantitative comparison of the performance of the forecasting algorithms studied. Results shown in that table were computed using a large test data set of approximately five months of data. Half of the data set was used for training, a quarter was used for verification, and the remainder was used for testing performance. The neural network with added averaging function provided the smallest mean absolute percent error of 1.26%. When implemented into the PMCS, the forecasting algorithm was converted to a short term forecast that is re-trained every 15 minutes and an accurate forecast is provided. By re-training the artificial neural network, significant reductions in forecast error were achieved.

Figure 61 shows the results of the forecasting algorithm for a one week time span in September 2014. The top plot represents the forecasted electrical demand and the corresponding actual demand as measured during the following 15 minute demand interval. The bottom plot summarizes the EVSE availability forecast. The testbed in which the algorithms were implemented contains six level II charging stations, so the horizontal line in the bottom plot of Figure 61 is set at six stations. Any time the forecast dips below this line, the forecast is marked with a red star. Negative forecasts represent a new demand peak and zero EVSE availability.

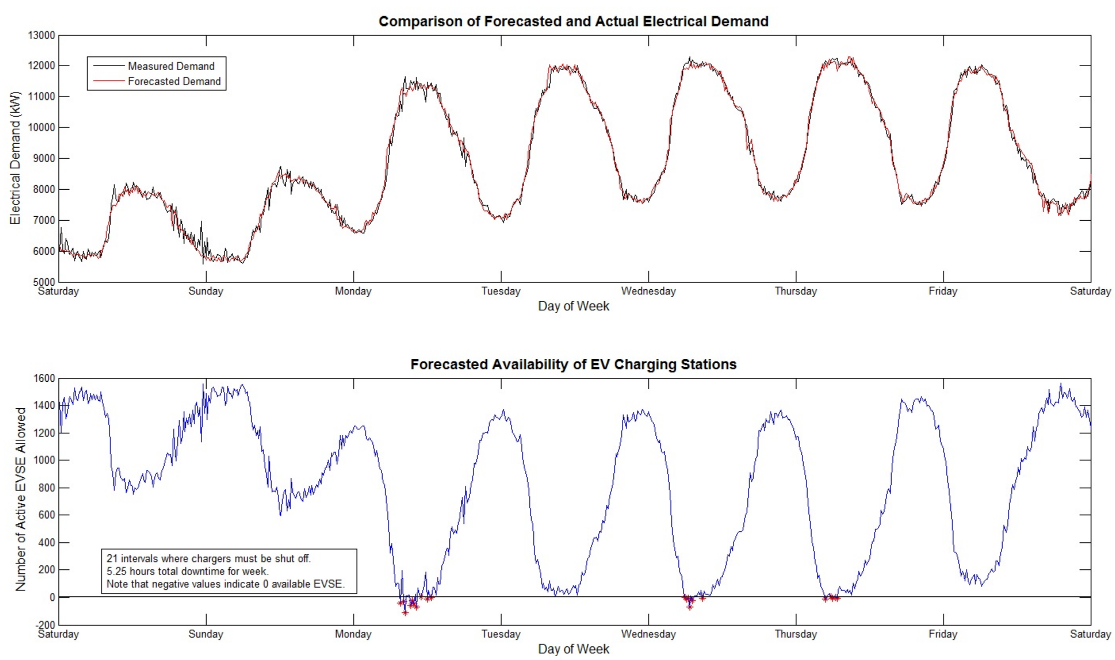



FIGURE 61: Forecasting results collected from PMCS after implementation at University of Louisville.

It can be seen that there are 3 days where the peak was experienced. During those days, there was a total of 21 15-minute intervals where charging was completely disabled. These periods are noted by a red star. This was equivalent to a total of 5.25 hours over the course of those three days where charging was disabled. The following week, which is not shown in Figure 61, was cooler and total electrical demand was less resulting in 0 demand intervals where charging was disabled.

The forecasting algorithm output shown in the top plot of Figure availforecast has an error associated with it as can be seen by the minor differences between the two data sets shown. The total error is calculated by finding the mean absolute percent difference between the forecasted electrical demand and the actual electrical demand as measured in the following 15 minute demand interval. Figure 62 represents the error calculated for the data set shown in Figure 61.

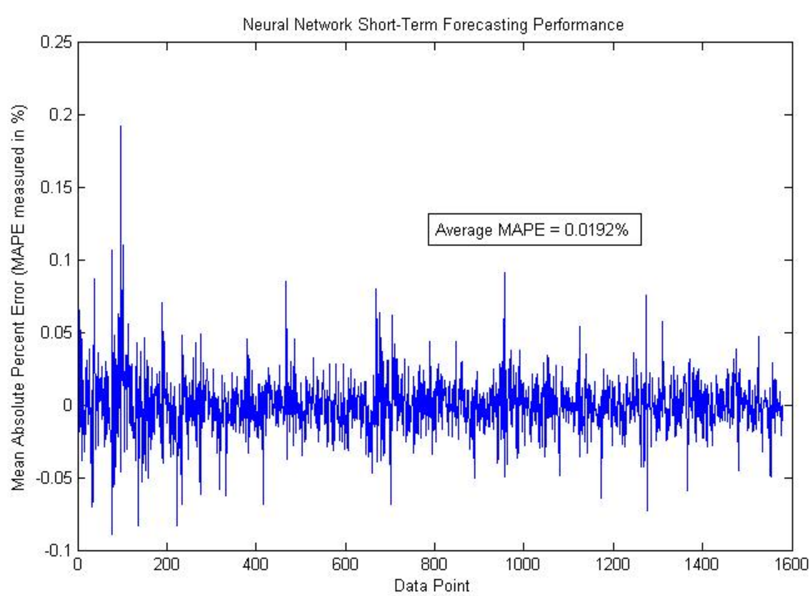



FIGURE 62: Forecasting algorithm percentage error for short-term forecast.

Due to the sinusoidal nature of electrical demand for the majority of commercial and industrial electric ratepayers, the demand peak falls within the typical demand windows set fourth by utility billing structures. Therefore, if EV charging activity occurs outside of the demand peak, no increases will be experienced in the demand charge as this is affected by the base electrical load only and not the EV infrastructure. However, forecasting error presents a possibility for EV charging activity to affect the electrical demand charge, however this is minimal compared to the uncontrolled charging scenario detailed in Table 1 of Chapter I. Through examination of the data collected after implementation of the PMCS, it was found that October 2014 provided the worst error of all months in the data set. The increase in error for October 2014 is due to the fact that September 2014 was unseasonably warm and humid and October was drastically different with unseasonably cool temperatures. This major drop off in temperature resulted in rare abnormalities in the electrical demand for October. Figure 63 shows the mean absolute percent error for all data points collected throughout the month of October 2014.

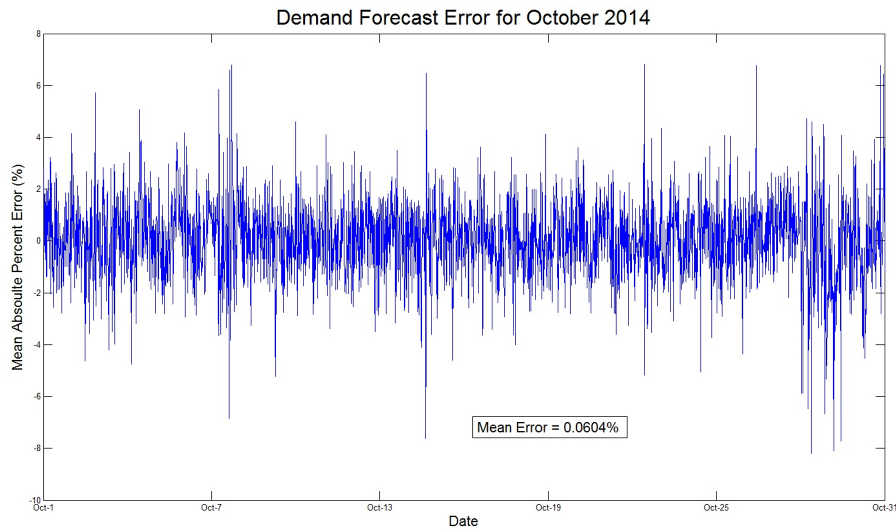



FIGURE 63: Mean absolute percent error for electrical demand forecast in October 2014.

The worst case MAPE in October 2014 of 0.0604% was then used to calculate the resultant electrical demand increase and associated costs. This error would be the only contributing factor for EV charging to affect the demand cost and resulting electrical costs, unless the control algorithm is overridden by a system administrator. Using the mean electrical demand for October 2014 of 7329 kVA, the mean absolute error due to the forecast is calculated to be 4.426 kVA. Assuming this error occurred during a peak demand event, and using the electrical rate structure for the University of Louisville, the resultant increase in electrical demand costs would be $61.71. Using this demand cost and associated electrical energy costs due to EV charging, the total cost of charging can be calculated. This is shown in Tables 14 through 16. Table 14 shows the effects uncontrolled charging can have on the electrical demand costs. Table 15 represents those same costs after the PMCS is implemented. Increases in electrical

TABLE 14

Calculated cost of uncontrolled charging activity.

| Number of EVs | C&I Energy Cost | C&I Demand Cost | C&I Total Cost |
|---|---|---|---|
| 1 | \$6.34 | \$51.58 | \$57.92 |
| 10 | \$63.40 | \$515.78 | \$579.18 |
| 100 | \$633.98 | \$5,157.80 | \$5,791.78 |
| 1000 | \$6,339.84 | \$51,578.00 | \$57,917.84 |

demand costs shown in this table are due to the forecasting error as calculated. Finally Table 16 compares the two total costs for uncontrolled and controlled EV charging. Significant reductions of nearly 90% are achieved as the penetration of EVs continues to grow.

Charge scheduling and prioritization is another primary piece of the PMCS. The charge prioritization module has no significant direct impact on the charging process other than the possibility to extend some charge times by 15 minutes to an hour depending on the size of possible electrical demand peaks that can occur. Therefore, no data was collected regarding the prioritization process during the implementation phase. Additionally, the scheduling algorithms presented in Chapter IV were not implemented at the University of Louisville due to lack of need for such an algorithm. Results for the scheduling and prioritization module are limited to simulations presented in Chapter IV.

TABLE 15

Calculated cost of controlled charging activity with forecast error considered.

| Number of EVs | C&I Energy Cost | C&I Demand Cost | C&I Total Cost |
|---|---|---|---|
| 1 | \$6.34 | \$61.71 | \$68.05 |
| 10 | \$63.40 | \$61.71 | \$125.11 |
| 100 | \$633.98 | \$61.71 | \$695.69 |
| 1000 | \$6,339.84 | \$61.71 | \$6,401.55 |

TABLE 16

Comparison of total cost of charging.

| Number of EVs | Uncontrolled Cost Increase | Controlled Cost Increase | Percent Difference |
|---|---|---|---|
| 1 | \$57.92 | \$68.05 | -17.49% |
| 10 | \$579.18 | \$125.11 | 78.40% |
| 100 | \$5,791.78 | \$695.69 | 87.99% |
| 1000 | \$57,917.84 | \$6,401.55 | 88.95% |

As the wireless ZigBee communication infrastructure is added to other charging stations, the capabilities of the PMCS can be expanded to their intended state. Nonetheless, implementing the power monitoring and control system into the EV charging testbed at the University of Louisville has provided valuable data to verify the simulations run throughout the development of the PMCS. The PMCS has proven to be a novel and intelligent control system that limits electrical demand increases therefore resulting in lower electrical costs to the commercial or industrial electric ratepayer. EVSE availability is maximized without increasing cost of daytime charging at the workplace.

## C. Suggestions for Future Work

There are several directions possible for future research related to the power monitoring and control system for EV charging activity. One such direction is to study other possible control methods such as model predictive control. The approach taken in this work was to subdivide the PMCS into a number of components, including: data collection, forecasting, scheduling, and control, and then find the best solution for each component individually. Other control system approaches such as model predictive control may provide similar or better results with a strategy that is much less complex.

The final forecasting model could be tuned to provide better performance. Resultant increases in electrical demand costs are a direct consequence of forecasting error. Figure 62 shows that the mean absolute percent error is quite small. However, the standard distribution of this error is still quite large. If the electrical demand forecast can be more accurate, the PMCS would benefit from lower operational costs. Furthermore, the EVSE availability is a calculated value that is based on the electrical demand forecast, therefore magnifying any error that is encountered. If this value can be a direct output of the forecasting algorithm, rather than a calculated result, improvements in error of EVSE availability can also be achieved.

Another area for future work is to develop a better user interface that can be installed on smart internet-enabled phones or accessed through the internet. This user interface could provide scheduling so EV owners could reserve a time slot throughout the day at a given EVSE. It could also inform EV owners of EVSE availability, and keep track of driving habits and statistics. A better user interface could also notify EV owners when a charge cycle is complete or notify them when peak demand events occur that may temporarily disable charging capability. EV owners could generate a user profile that specifies state of charge required by the end of the charging cycle in the event that 100% battery capacity is not required. Additionally, the profile could specify times when the EV charge cycle must be complete. The profile could be beneficial to the scheduling and prioritization module of the PMCS.

Expanding the capabilities of the PMCS to handle EV charging facilities in multiple locations that may be separated by distances too far for traditional ZigBee wireless networking to reach is another future direction that should be studied. This could be completed by adding an internet or cellular interface to the EVSE nodes. This would allow for EV charging stations to me managed from any location. For example, a large metropolitan college with several campuses located in a city may choose to have EVSE available on each campus, but may wish to have a single master controller that can monitor and control all stations simultaneously. Or another example could be a restaurant chain that has locations throughout the United States but wants to make EV charging available to their patrons. Patrons could use the web interface to check for availability and schedule charging windows at any location.

A fourth area for future work would be to expand the capabilities of the PMCS to work with EVSE from various manufacturers. Currently, the PMCS is designed to work with the General Electric EVSE, however a universal node may be designed that can work with any EVSE, regardless of the manufacturer. This could be a universal wireless or cellular device that simply attaches to any charging station and controls the power flow to the vehicle through an electrical contact. For the PMCS to be a marketable solution, a universal node would be required.

Research could be completed to search for other applications that may benefit from such a technology. For example, large industrial businesses that have significant electric forklift fleets may benefit from a system similar to the PMCS. For example, at the end of a shift, all electric forklifts are parked and plugged in to charge. This surge in electrical demand can create new demand peaks which result in significant increases in electricity prices per unit. A system such as the PMCS could control and schedule charging to minimize the effects caused by plugging in all forklifts at once.

Finally, one last area that would be of value to the PMCS is to implement Vehicle-to-Grid (V2G) and Vehicle-to-Vehicle (V2V) charge sharing technologies. Currently, the power electronics installed in plug-in hybrid electric vehicles only allow for one way flow of electrical power from the grid to the battery system. If these power electronics could be modified to allow two way power flow, PHEVs could be utilized for large scale grid energy storage. This would be beneficial to help minimize demand peaks and shift electrical loads to level electrical demand profiles. V2V would be beneficial to the PMCS because vehicles requiring charge during peak demand periods could receive power from other vehicles that are already fully charged or may not require a full charge until later.

Each of these future directions could be extremely valuable to the future development of the PMCS. There are numerous possibilities for the PMCS as it lays the foundation required for several other possible smart grid technologies.

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# APPENDICES I

## Matlab *urlread_auth* m-file

```
function [s,info] = urlread_auth(url, user, password)
%URLREAD_AUTH Like URLREAD, with basic authentication
%
% [s,info] = urlread_auth(url, user, password)
%
% Returns bytes. Convert to char if you're retrieving text.
%
% Examples:
% sampleUrl = 'http://browserspy.dk/password-ok.php';
% [s,info] = urlread_auth(sampleUrl, 'test', 'test');
% txt = char(s)

% Matlab's urlread() doesn't do HTTP Request params, so work
% directly with Java
jUrl = java.net.URL(url);
conn = jUrl.openConnection();
conn.setRequestProperty('Authorization',...
    ['Basic ' base64encode([user ':' password])]);
conn.connect();
info.status = conn.getResponseCode();
```

```
info.errMsg = char(readstream(conn.getErrorStream()));
s = readstream(conn.getInputStream());

function out = base64encode(str)
% Uses Sun-specific class, but we know that is the JVM Matlab uses
encoder = sun.misc.BASE64Encoder();
out = char(encoder.encode(java.lang.String(str).getBytes()));

%%
function out = readstream(inStream)
%READSTREAM Read all bytes from stream to uint8
try
    import com.mathworks.mlwidgets.io.InterruptibleStreamCopier;
    byteStream = java.io.ByteArrayOutputStream();
    isc = InterruptibleStreamCopier.getInterruptibleStreamCopier();
    isc.copyStream(inStream, byteStream);
    inStream.close();
    byteStream.close();
    out = typecast(byteStream.toByteArray', 'uint8'); %'
catch err
    out = []; %HACK: quash
end
```

APPENDICES II

Combined Matlab m-file Including Data Collection and Forecasting Modules

```
clc
clear all
load('TestData.mat')
%%
% Gather Information and update database

    % Steam Plant Power (in VA)
    Url = 'http://136.165.235.192/text/query/props?/BelknapES/...
    Steam_Cw_Plant/CBank_Plant/Data/Apparent_Power.presentValue';
    [s] = urlread_auth(Url, 'speed', 'speed');
    readstring = char(s);
    SteamCW_VA_Demand=str2num(readstring(1:length(readstring)-4));

    % Campus Power (in VA)
    Url = 'http://136.165.235.192/text/query/props?/BelknapES/...
    Steam_Cw_Plant/CBank_Campus/Data/Apparent_Power.presentValue';
    [s] = urlread_auth(Url, 'speed', 'speed');
    readstring = char(s);
    Campus_VA_Demand=str2num(readstring(1:length(readstring)-4));

```

```
    Total_Power=SteamCW_VA_Demand+Campus_VA_Demand;

    % read in time and date
    date_time=clock;
    D=[num2str(date_time(1)) '-' num2str(date_time(2)) '-' ...
        num2str(date_time(3))];
    dayofweek=weekday(D);

    % Read in temperature
    Url = 'http://136.165.235.192/text/query/props?/BelknapES/...
    Natatorium_Graphics/HtgClg_Systems/CHWS/Data/OaT.presentValue';
    [s] = urlread_auth(Url, 'speed', 'speed');
    readstring = char(s);
    temp=str2num(readstring(1:length(readstring)-3)); %#ok<ST2NM>

    % Read in dewpoint
    Url = 'http://136.165.235.192/text/query/props?/BelknapES/...
    Natatorium_Graphics/HtgClg_Systems/CHWS/Data/OaRh.presentValue';
    [s] = urlread_auth(Url, 'speed', 'speed');
    readstring = char(s);
    relhum=str2num(readstring(1:length(readstring)-3)); %#ok<ST2NM>
    % calculate dewpoint from relative humidity
    dewpoint=243.04*(log(relhum/100)+((17.625*temp)/(243.04+temp)))...
        /(17.625-log(relhum/100)-((17.625*temp)/(243.04+temp)));

    %Get last power and 2 hour average power readings from database
    Last_Power=data(end,8);
```

```
Power_Avg=mean(data(end-7:end,8));

% Generate vector of present readings
present_readings=[date_time(2:5),dayofweek,temp,dewpoint,...
    Total_Power,Last_Power,Power_Avg];

% Manipulate database of 9001 elements (approx 3 months)
data(1:9000,:)=data(2:9001,:); %shift elements
data(9001,1:10)=present_readings; %add new readings

datatarget(1:9000,1)=datatarget(2:9001,1); %shift training targets
datatarget(9000,1)=Total_Power; %Add last power reading for target
datatarget(9001,1)=0; %Next power reading will be taken at next int.

%calculate max power for this billing period
clear data_subset;
clear data_index;
if date_time(3)==1 %if first day of month
    % max demand is 85% of max demand from previous month
    if date_time(2)-1==0
        month=12;
    else
        month=date_time(2)-1;
    end
    data_index=(data(:,1)==month);
    data_subset=data(data_index,:);
    max_demand=0.85*max(data_subset(:,8));
```

```
    else
        % calculate max demand for current month
        data_index=(data(:,1)==date_time(2));
        data_subset=data(data_index,:);
        max_demand=max(data_subset(:,8));
    end

%%
% Generate forecast of short term electric demand

% This script assumes these variables are defined:
%   data - input data.
%   datatarget - target data.

inputs = data(1:9000,:)';
targets = datatarget(1:9000,1)';

% Create a Fitting Network
hiddenLayerSize = 30;
net = fitnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};


```

```
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% For help on training function 'trainlm' type: help trainlm
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainlm';  % Levenberg-Marquardt

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
  'plotregression', 'plotfit'};


% Train the Network
net.trainParam.showWindow = false; % comment to see the NN train. perf.
[net,tr] = train(net,inputs,targets);

% Test the Network
```

```
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs);

% Recalculate Training, Validation and Test Performance
trainTargets = targets .* tr.trainMask{1};
valTargets = targets  .* tr.valMask{1};
testTargets = targets  .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,outputs); %uncomment
valPerformance = perform(net,valTargets,outputs); %uncomment
testPerformance = perform(net,testTargets,outputs); %uncomment

% View the Network
%view(net); %uncomment

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotfit(net,inputs,targets)
%figure, plotregression(targets,outputs)
%figure, ploterrhist(errors)

% [n,x]=hist(errors,128);
% plot(x,n)
% err = targets-outputs;
% errpct = abs(err)./targets*100;
```

```
% MAE = mean(abs(err))
% MAPE = mean(errpct(~isinf(errpct)))
% figure;
% hold on;
% plot(nntargetnew, 'b')
% plot(outputs, 'r')


%%
% Determine number of charging stations allowed to be active

next_demand_value=net(data(9001,:)')
num_stations=(max_demand-next_demand_value)/3.3
data(9001,11)=next_demand_value;
data(9001,12)=num_stations;

%%
% Run Scheduling Algorithm if #vehicles > #stations

% *** Scheduling Algorithm here *** %

%%
% Send control signals to stations

% *** Serial Communication Algorithm here *** %

clearvars -except data datatarget max_demand ChargerDemand
```

```
save('TestData')
```

APPENDICES III

Non-Preemptive SA Scheduling Algorithm m-file

```
% EV Scheduling Non-Preemptive SA

%%
clearvars -EXCEPT Results ResultsTest time timetest;
%close all;
clc;

load('TestData.mat');

for setupi=1:6
%set up number of vehicles
numvehicles=setup(1,setupi);  % can also use 80 here
nummachines=setup(2,setupi);
offset=setup(3,setupi);
index1=setup(4,setupi);
index2=setup(5,setupi);
if nummachines==3
    machinesavail=machines3;
elseif nummachines==5
    machinesavail=machines5;
```

```
elseif nummachines==6
    machinesavail=machines6;
else
    machinesavail=machines20;
end

% Create machine available matrix
machines=zeros(nummachines,2);
for i=1:96
    if machinesavail(i)<nummachines
        numberdown=nummachines-machinesavail(i);
        for j=1:numberdown
            if machines(j,1)==0
                machines(j,1)=i*0.25;
            else
                machines(j,1)=machines(j,1);
            end
            machines(j,2)=(i+1)*0.25;
        end
    end
end

%%

vehicle=struct('ArrivalTime',{},'SOCReq',{},'ProcessingTime',{},...
'ScheduledStart',{},'ScheduledMachine',{},'JobNumber',{},...
'DesiredCompletion',{},'DemandDelays',{});
```

```


% Main loop to loop through 10 sets of test data
%%
for index=index1:index2
    tic;
    vehicles=TestData{index};

    numkeep=0;

    % Set up vehicle objects using data structure above
    for i=1:numvehicles
        vehicle(i).ArrivalTime=vehicles(i,1);
        vehicle(i).SOCReq=vehicles(i,2);
        vehicle(i).ProcessingTime=vehicles(i,4);
        vehicle(i).ScheduledStart=vehicles(i,3);
        vehicle(i).DesiredCompletion=vehicles(i,5);
        vehicle(i).DemandDelays=0;
    end


    mastervehicle=vehicle;

    %%
    %%
    % Determine best starting point (multistart)
    swap=randi([0 10],1,1);
```

```
    num=100; %Number of entries to create in neighborhood function
    x=1;
    neighborhood=cell(num+1,4);
    for count=1:num
        vehicle=mastervehicle; %reset vehicle matrix
        Schedule=zeros(nummachines,3); % 2nd col = total proc. time,
        % 3rd col is # jobs
        % 1st column of schedule matrix is machine number:
        for i=1:nummachines
            Schedule(i,1)=i;
        end

        for i=1:numvehicles
            swap=randi([0 10],1,1);
            k=5;
            if swap>=k
                %generate random machine
                randmachine=randi([1 nummachines],1,1);
                starttime=Schedule(randmachine,2);

                % Schedule next job to random machine
                %update sched start time
                vehicle(i).ScheduledStart=...
                    max(vehicle(i).ScheduledStart,starttime);
                %update total proc. time
                Schedule(randmachine,2)=vehicle(i).ScheduledStart+...
                    vehicle(i).ProcessingTime;
```

```
            %add 1 job to machine
            Schedule(randmachine,3)=Schedule(randmachine,3)+1;
            %define which machine the job is sched at.
            vehicle(i).ScheduledMachine=randmachine;
            vehicle(i).JobNumber=Schedule(randmachine,3);

        else
            % Find machine with least processing time remaining
            nextavail=min(Schedule(:,2));
            for j=1:nummachines
                if Schedule(j,2)==nextavail
                    nextmachine=Schedule(j,1);
                end
            end

            % Schedule next job to mach. with least proc. time rem.
            %update sched start time
            vehicle(i).ScheduledStart=...
                max(vehicle(i).ScheduledStart,nextavail);
            %update total proc. time
            Schedule(nextmachine,2)=vehicle(i).ScheduledStart+...
                vehicle(i).ProcessingTime;
            %add 1 job to machine
            Schedule(nextmachine,3)=Schedule(nextmachine,3)+1;
            %define which machine the job is sched at.
            vehicle(i).ScheduledMachine=nextmachine;
            vehicle(i).JobNumber=Schedule(nextmachine,3);
```

```
            end
                % repeat until all jobs scheduled
        end
    %Adjust sched. to account for machines down due to demand charge

    %For each demand interval i, check to see how many machines are avail.
    % There are 96 demand intervals in 1 day

    vehicleNoDemand=vehicle;
    TotalIntervalsDelayed=0;
    for i=1:nummachines
        intstart=machines(i,1);
        intend=machines(i,2);
        for j=1:numvehicles
            if vehicle(j).ScheduledMachine==i && ...
                    vehicle(j).ScheduledStart<intend && ...
                    vehicle(j).ScheduledStart+...
                    vehicle(j).ProcessingTime>intstart %if job overlaps
                totaldelay=intend-vehicle(j).ScheduledStart;
                vehicle(j).ScheduledStart=intend;
                TotalIntervalsDelayed=TotalIntervalsDelayed+...
                    floor(totaldelay/0.25);
                % adjust jobs scheduled after job j
                for k=1:numvehicles
                    if vehicle(k).ScheduledMachine==...
                            vehicle(j).ScheduledMachine && ...
                            vehicle(k).JobNumber>vehicle(j).JobNumber
```

```
                        vehicle(k).ScheduledStart=...
                            vehicle(k).ScheduledStart+totaldelay;
                    end
                end
            end
        end
    end
        % Check to see # jobs are not complete due to due date and proc.
        % time mismatch:
        ChargeNotComp=0;
        for i=1:numvehicles
            if vehicle(i).ScheduledStart+vehicle(i).ProcessingTime>...
                    vehicle(i).DesiredCompletion
                ChargeNotComp=ChargeNotComp+1;
            end
        end
        LatestChargeStopped=max([vehicle.ScheduledStart]+...
            [vehicle.ProcessingTime]);

        neighborhood{x,1}=vehicle;
        neighborhood{x,2}=Schedule;
        neighborhood{x,3}=ChargeNotComp;
        neighborhood{x,4}=LatestChargeStopped;
        neighborhood{x,5}=vehicleNoDemand;
        x=x+1;
    end
    Schedule=zeros(nummachines,3); % 2nd col = total proc. time,
```

```
% 3rd col is # jobs
% 1st column of schedule matrix is machine number:
for i=1:nummachines
    Schedule(i,1)=i;
end
vehicle=mastervehicle;
for i=1:numvehicles
    % Find machine with least processing time remaining
    nextavail=min(Schedule(:,2));
    for j=1:nummachines
        if Schedule(j,2)==nextavail
            nextmachine=Schedule(j,1);
        end
    end

    % Schedule next job to machine with least proc. time remaining
    %update sched start time
    vehicle(i).ScheduledStart=max(vehicle(i).ScheduledStart,...
        nextavail);
    %update total proc. time
    Schedule(nextmachine,2)=vehicle(i).ScheduledStart+...
        vehicle(i).ProcessingTime;
    %add 1 job to machine
    Schedule(nextmachine,3)=Schedule(nextmachine,3)+1;
    %define which machine the job is sched at.
    vehicle(i).ScheduledMachine=nextmachine;
    vehicle(i).JobNumber=Schedule(nextmachine,3);
```

```
    end
    %Adjust sched.  for machines that are down due to dem. charge

    %For each demand interval i, check to see # machines are avail.
    % There are 96 demand intervals in 1 day

    vehicleNoDemand=vehicle;
    TotalIntervalsDelayed=0;
    for i=1:nummachines
        intstart=machines(i,1);
        intend=machines(i,2);
        for j=1:numvehicles
            if vehicle(j).ScheduledMachine==i && ...
                    vehicle(j).ScheduledStart<intend && ...
                    vehicle(j).ScheduledStart+...
                    vehicle(j).ProcessingTime>intstart %if job overlaps
                totaldelay=intend-vehicle(j).ScheduledStart;
                vehicle(j).ScheduledStart=intend;
                TotalIntervalsDelayed=TotalIntervalsDelayed+...
                    floor(totaldelay/0.25);
                % adjust jobs scheduled after job j
                for k=1:numvehicles
                    if vehicle(k).ScheduledMachine==...
                            vehicle(j).ScheduledMachine && ...
                            vehicle(k).JobNumber>vehicle(j).JobNumber
                        vehicle(k).ScheduledStart=...
                            vehicle(k).ScheduledStart+totaldelay;
```

```
                    end
                end
            end
        end
    end

    % Check to see # jobs are not complete due to due date and processing
    % time mismatch:
    ChargeNotComp=0;
    for i=1:numvehicles
        if vehicle(i).ScheduledStart+vehicle(i).ProcessingTime>...
                vehicle(i).DesiredCompletion
            ChargeNotComp=ChargeNotComp+1;
        end
    end
    LatestChargeStopped=max([vehicle.ScheduledStart]+...
        [vehicle.ProcessingTime]);

    neighborhood{num+1,1}=vehicle;
    neighborhood{num+1,2}=Schedule;
    neighborhood{num+1,3}=ChargeNotComp;
    neighborhood{num+1,4}=LatestChargeStopped;
    neighborhood{num+1,5}=vehicleNoDemand;

    %%
    %Sort multiple starting schedules to determine fastest with least
    %ammount of unfinished jobs
```

```
    neighborhood=sortrows(neighborhood,3);
    neighborhood=sortrows(neighborhood,4);

    %Assign best schedule to vehicle matrix.
    clear vehicle;
    clear vehicleNoDemand;
    clear vehiclebackupdemand;
    vehicle=neighborhood{1,1};
    vehiclebackupdemand=vehicle;
    vehicleNoDemand=neighborhood{1,5};


    %%
    %Perform job swapping to try to optimize the solution

    LatestChargeStopped=max([vehicle.ScheduledStart]+...
        [vehicle.ProcessingTime]);

    vehicle=vehicleNoDemand;

    %Loop through this process n times
    numswaps=0;
    n=0;
    iterations=20000;
    N=iterations;
    %Tn=0.61;
    T0=15;
```

```
alpha=-.36;
error=100;
ebest=LatestChargeStopped;
while n<iterations %&& error>0.0001
    vehiclebackup=vehicle;
    % make backup of schedule if change is not accepted
    clear rj1;
    clear rj2;
    % Pick random job number 1
    rj1=randi([1 numvehicles],1,1);
    rj2=rj1;
    % Pick random job number 2
    while rj2==rj1
        rj2=randi([1 numvehicles],1,1);
        %verifies that 2nd job is different from first
    end
    % Check feasibility of swap
    if vehicle(rj1).ArrivalTime<=vehicle(rj2).ScheduledStart && ...
            vehicle(rj2).ArrivalTime<=vehicle(rj1).ScheduledStart
        % Make swap
        job1=vehicle(rj1);
        % temporarily store job info to make swap easier
        job2=vehicle(rj2);
        vehicle(rj1).ScheduledMachine=job2.ScheduledMachine;
        vehicle(rj1).JobNumber=job2.JobNumber;
        vehicle(rj2).ScheduledMachine=job1.ScheduledMachine;
        vehicle(rj2).JobNumber=job1.JobNumber;
```

```
            vehicle(rj1).ScheduledStart=job2.ScheduledStart;
            vehicle(rj2).ScheduledStart=job1.ScheduledStart;

            % Adjust affected jobs
            for k=1:numvehicles
                if vehicle(k).ScheduledMachine==...
                        vehicle(rj1).ScheduledMachine && ...
                        vehicle(k).JobNumber>vehicle(rj1).JobNumber
                    % Find jobs on machine after swapped job
                    vehicle(k).ScheduledStart=...
                        max(vehicle(k).ArrivalTime, ...
                        vehicle(k).ScheduledStart-...
                        (vehicle(rj2).ProcessingTime-...
                        vehicle(rj1).ProcessingTime));
                end
            end
            for k=1:numvehicles
                if vehicle(k).ScheduledMachine==...
                        vehicle(rj2).ScheduledMachine && ...
                        vehicle(k).JobNumber>vehicle(rj2).JobNumber
                    % Find jobs on machine after swapped job
                    vehicle(k).ScheduledStart=...
                        max(vehicle(k).ArrivalTime, ...
                        vehicle(k).ScheduledStart-...
                        (vehicle(rj1).ProcessingTime-...
                        vehicle(rj2).ProcessingTime));
                end
```

```
            end

            vehicleNoDemand=vehicle;

            % Add demand interval delays back in
            for i=1:nummachines
                intstart=machines(i,1);
                intend=machines(i,2);
                for j=1:numvehicles
                    if vehicle(j).ScheduledMachine==i && ...
                            vehicle(j).ScheduledStart<intend && ...
                            vehicle(j).ScheduledStart+...
                            vehicle(j).ProcessingTime>intstart %if job overlaps
                        totaldelay=intend-vehicle(j).ScheduledStart;
                        vehicle(j).ScheduledStart=intend;
                        % adjust jobs scheduled after job j
                        for k=1:numvehicles
                            if vehicle(k).ScheduledMachine==...
                                    vehicle(j).ScheduledMachine && ...
                                    vehicle(k).JobNumber>...
                                    vehicle(j).JobNumber
                                vehicle(k).ScheduledStart=...
                                    vehicle(k).ScheduledStart+totaldelay;
                            end
                        end
                    end
                end
```

```
            end

            % Determine whether or not to keep the change
            % Calculate T
            T=T0*exp(alpha*n);
            %T=(T0/Tn)^(n/iterations);

            LatestChargeStoppedNew=max([vehicle.ScheduledStart]+...
                [vehicle.ProcessingTime]);
            if LatestChargeStoppedNew<=LatestChargeStopped
                %Keep Change
                numswaps=numswaps+1;
                LatestChargeStopped=LatestChargeStoppedNew;
                ebest=LatestChargeStopped;
                vehiclefinal=vehicle;
                vehicle=vehicleNoDemand;
            elseif exp(-(LatestChargeStoppedNew-LatestChargeStopped)/T)...
                    >rand(1)
                % Keep Change
                numswaps=numswaps+1;
                LatestChargeStopped=LatestChargeStoppedNew;
                ebest=LatestChargeStopped;
                vehiclefinal=vehicle;
                vehicle=vehicleNoDemand;
                numkeep=numkeep+1;
            else
                % Discard changes
```

```
                vehicle=vehiclebackup;
                clear vehicleNoDemand;
            end

        end
        n=n+1;
    end
    %vehiclefinal=vehicle;
    %disp(['The total number of job swaps: ', num2str(numswaps)])
    ChargeNotComp=0;
    for i=1:numvehicles
        if vehicle(i).ScheduledStart+vehicle(i).ProcessingTime>...
                vehicle(i).DesiredCompletion
            ChargeNotComp=ChargeNotComp+1;
        end
    end

    vehicle=vehiclefinal;

    if numkeep==0
        clear vehicle;
        vehicle=vehiclebackupdemand;
        ebest=max([vehicle.ScheduledStart]+[vehicle.ProcessingTime])
        disp(['Case: ', num2str((setupi-1)*10+index)])
    end

    Results{8,index+offset}=ebest-vehicle(1).ArrivalTime; %makespan
```

```
    Results{9,index+offset}=vehicle;
    time(4,index+offset)=toc;
end
end
```

APPENDICES IV

Preemptive SA Scheduling Algorithm m-file

```
% EV Scheduling Preemptive SA (jobs can be paused)

%%
clearvars -EXCEPT Results ResultsTest time timetest;
%close all;
clc;

load('TestData.mat');

for setupi=1:6
%set up number of vehicles
numvehicles=setup(1,setupi);  % can also use 80 here
nummachines=setup(2,setupi);
offset=setup(3,setupi);
index1=setup(4,setupi);
index2=setup(5,setupi);
if nummachines==3
    machinesavail=machines3;
elseif nummachines==5
    machinesavail=machines5;
```

```
elseif nummachines==6
    machinesavail=machines6;
else
    machinesavail=machines20;
end

%%

vehicle=struct('ArrivalTime',{},'SOCReq',{},'ProcessingTime',{},...
'ScheduledStart',{},'ScheduledMachine',{},'JobNumber',{},...
'DesiredCompletion',{},'DemandDelays',{});


% Main loop to loop through 10 sets of test data
%%
for index=index1:index2
    tic;
    vehicles=TestData{index};

    numkeep=0;

    % Set up vehicle objects using data structure above
    for i=1:numvehicles
        vehicle(i).ArrivalTime=vehicles(i,1);
        vehicle(i).SOCReq=vehicles(i,2);
        vehicle(i).ProcessingTime=vehicles(i,4);
        vehicle(i).ScheduledStart=vehicles(i,3);
```

```
        vehicle(i).DesiredCompletion=vehicles(i,5);
        vehicle(i).DemandDelays=0;
    end


    mastervehicle=vehicle;

    %%
    %%
    % Determine best starting point (multistart)
    swap=randi([0 10],1,1);
    num=100; %Number of entries to create in neighborhood function
    x=1;
    neighborhood=cell(num+1,5);
    for count=1:num
        vehicle=mastervehicle; %reset vehicle matrix
        Schedule=zeros(nummachines,3); % 2nd col = total proc. time,
        % 3rd col is # jobs
        % 1st column of schedule matrix is machine number:
        for i=1:nummachines
            Schedule(i,1)=i;
        end

        for i=1:numvehicles
            swap=randi([0 10],1,1);
            k=5;
            if swap>=k
```

```
            %generate random machine
            randmachine=randi([1 nummachines],1,1);
            starttime=Schedule(randmachine,2);

            % Schedule next job to random machine
            %update sched start time
            vehicle(i).ScheduledStart=...
                max(vehicle(i).ScheduledStart,starttime);
            %update total proc. time
            Schedule(randmachine,2)=vehicle(i).ScheduledStart+...
                vehicle(i).ProcessingTime;
            %add 1 job to machine
            Schedule(randmachine,3)=Schedule(randmachine,3)+1;
            %define which machine the job is sched at.
            vehicle(i).ScheduledMachine=randmachine;
            vehicle(i).JobNumber=Schedule(randmachine,3);

        else
            % Find machine with least processing time remaining
            nextavail=min(Schedule(:,2));
            for j=1:nummachines
                if Schedule(j,2)==nextavail
                    nextmachine=Schedule(j,1);
                end
            end

            % Schedule next job to machine with least proc. time rem.
```

```
                %update sched start time
                vehicle(i).ScheduledStart=...
                    max(vehicle(i).ScheduledStart,nextavail);
                %update total proc. time
                Schedule(nextmachine,2)=vehicle(i).ScheduledStart+...
                    vehicle(i).ProcessingTime;
                %add 1 job to machine
                Schedule(nextmachine,3)=Schedule(nextmachine,3)+1;
                %define which machine the job is sched at.
                vehicle(i).ScheduledMachine=nextmachine;
                vehicle(i).JobNumber=Schedule(nextmachine,3);
            end
                % repeat until all jobs scheduled
        end
    %Adjust schedule to account for machines down due to demand charge

    %For each demand interval i, check to see how many machines are avail.
    % There are 96 demand intervals in 1 day

    vehicleNoDemand=vehicle;
    TotalIntervalsDelayed=0;
    for i=1:96
        if machinesavail(i)~=nummachines
            numberdown=nummachines-machinesavail(i);
            % Pick numberdown machines to pause charging
            % for 1 demand interval (15 minutes)
            % Look at which jobs currently scheduled during that
```

```
        % demand interval and see which will be completed first
        % and add 15 minutes to it.
        for j=1:numberdown
            mintimerem=24;
            for k=1:numvehicles
                % check to see if job falls in window
                if vehicle(k).ScheduledStart<=(i/4) && ...
                        vehicle(k).ScheduledStart+...
                        vehicle(k).ProcessingTime>=(i/4)
                    %Find job with least time remaining
                    if vehicle(k).ScheduledStart+...
                            vehicle(k).ProcessingTime-(i/4)<=mintimerem
                        mintimerem=vehicle(k).ScheduledStart+...
                            vehicle(k).ProcessingTime-(i/4);
                        %keep track of job with least time remaining
                        vehicletodelay=k;
                    end
                end
            end

            %Update proc. times and properties on affected vehicle
            vehicle(vehicletodelay).ProcessingTime=...
                vehicle(vehicletodelay).ProcessingTime+0.25;
            vehicle(vehicletodelay).DemandDelays=...
                vehicle(vehicletodelay).DemandDelays+1;
            TotalIntervalsDelayed=TotalIntervalsDelayed+1;
            machinenum=vehicle(vehicletodelay).ScheduledMachine;
```

```
                jobnum=vehicle(vehicletodelay).JobNumber;

                %Delay scheduled start for later jobs on affected machine
                for k=1:numvehicles
                    if vehicle(k).ScheduledMachine==machinenum && ...
                            vehicle(k).JobNumber>jobnum
                        vehicle(k).ScheduledStart=...
                            vehicle(k).ScheduledStart+.25;
                    end
                end
            end
        end
    end

        % Check to see # jobs are not complete due to due date and proc.
        % time mismatch:
        ChargeNotComp=0;
        for i=1:numvehicles
            if vehicle(i).ScheduledStart+vehicle(i).ProcessingTime>...
                    vehicle(i).DesiredCompletion
                ChargeNotComp=ChargeNotComp+1;
            end
        end
        LatestChargeStopped=max([vehicle.ScheduledStart]+...
            [vehicle.ProcessingTime]);

        neighborhood{x,1}=vehicle;
```

```
        neighborhood{x,2}=Schedule;
        neighborhood{x,3}=ChargeNotComp;
        neighborhood{x,4}=LatestChargeStopped;
        neighborhood{x,5}=vehicleNoDemand;
        x=x+1;
    end
    vehicle=mastervehicle;
    Schedule=zeros(nummachines,3); % 2nd col = total proc. time,
    % 3rd col is # jobs
    % 1st column of schedule matrix is machine number:
    for i=1:nummachines
        Schedule(i,1)=i;
    end
    for i=1:numvehicles
        % Find machine with least processing time remaining
        nextavail=min(Schedule(:,2));
        for j=1:nummachines
            if Schedule(j,2)==nextavail
                nextmachine=Schedule(j,1);
            end
        end

        % Schedule next job to machine with least proc. time remaining
        %update sched start time
        vehicle(i).ScheduledStart=max(vehicle(i).ScheduledStart,nextavail);
        %update total proc. time
        Schedule(nextmachine,2)=vehicle(i).ScheduledStart+...
```

```
            vehicle(i).ProcessingTime;
        %add 1 job to machine
        Schedule(nextmachine,3)=Schedule(nextmachine,3)+1;
        %define which machine the job is sched at.
        vehicle(i).ScheduledMachine=nextmachine;
        vehicle(i).JobNumber=Schedule(nextmachine,3);
    end




    %%
    %Adjust sched. to account for machines down due to demand charge

    %For each demand interval i, check to see how many machines are avail.
    % There are 96 demand intervals in 1 day

    vehicleNoDemand=vehicle;
    TotalIntervalsDelayed=0;
    for i=1:96
        if machinesavail(i)~=nummachines
            numberdown=nummachines-machinesavail(i);
            % Pick numberdown machines to pause charging
            % for 1 demand interval (15 minutes)
            % Look at which jobs currently scheduled during that
            % demand interval and see which will be completed first
            % and add 15 minutes to it.
```

```
for j=1:numberdown
    mintimerem=24;
    for k=1:numvehicles
        % check to see if job falls in window
        if vehicle(k).ScheduledStart<=(i/4) && ...
                vehicle(k).ScheduledStart+...
                vehicle(k).ProcessingTime>=(i/4)
            if vehicle(k).ScheduledStart+...
                    vehicle(k).ProcessingTime-(i/4)<=...
                    mintimerem %Find job with least time rem.
                mintimerem=vehicle(k).ScheduledStart+...
                    vehicle(k).ProcessingTime-(i/4);
                %keep track of job with least time remaining
                vehicletodelay=k;
            end
        end
    end

    %Update proc. times and properties on affected vehicle
    vehicle(vehicletodelay).ProcessingTime=...
        vehicle(vehicletodelay).ProcessingTime+0.25;
    vehicle(vehicletodelay).DemandDelays=...
        vehicle(vehicletodelay).DemandDelays+1;
    TotalIntervalsDelayed=TotalIntervalsDelayed+1;
    machinenum=vehicle(vehicletodelay).ScheduledMachine;
    jobnum=vehicle(vehicletodelay).JobNumber;

```

```
                %Delay scheduled start for later jobs on affected machine
                for k=1:numvehicles
                    if vehicle(k).ScheduledMachine==machinenum && ...
                            vehicle(k).JobNumber>jobnum
                        vehicle(k).ScheduledStart=...
                            vehicle(k).ScheduledStart+.25;
                    end
                end
            end
        end
    end

    % Check to see # jobs are not complete due to due date and processing
    % time mismatch:
    ChargeNotComp=0;
    for i=1:numvehicles
        if vehicle(i).ScheduledStart+vehicle(i).ProcessingTime>...
                vehicle(i).DesiredCompletion
            ChargeNotComp=ChargeNotComp+1;
        end
    end
    LatestChargeStopped=max([vehicle.ScheduledStart]+...
        [vehicle.ProcessingTime]);


    neighborhood{num+1,1}=vehicle;
    neighborhood{num+1,2}=Schedule;
```

```
    neighborhood{num+1,3}=ChargeNotComp;
    neighborhood{num+1,4}=LatestChargeStopped;
    neighborhood{num+1,5}=vehicleNoDemand;
    %%
    %Sort multiple starting schedules to determine fastest with least
    %ammount of unfinished jobs
    neighborhood=sortrows(neighborhood,3);
    neighborhood=sortrows(neighborhood,4);

    %Assign best schedule to vehicle matrix.
    clear vehicle;
    clear vehicleNoDemand;
    clear vehiclebackupdemand;
    vehicle=neighborhood{1,1};
    vehiclebackupdemand=vehicle;
    vehicleNoDemand=neighborhood{1,5};

    %%
    %Perform job swapping to try to optimize the solution

    LatestChargeStopped=max([vehicle.ScheduledStart]+...
        [vehicle.ProcessingTime]);

    vehicle=vehicleNoDemand;

    %Loop through this process n times
    numswaps=0;
```

```
n=0;
iterations=20000;
N=iterations;
%Tn=0.61;
T0=15;
alpha=-.36;
error=100;
ebest=LatestChargeStopped;
while n<iterations %&& error>0.0001
    % make backup of schedule if change is not accepted
    vehiclebackup=vehicle;
    clear rj1;
    clear rj2;
    % Pick random job number 1
    rj1=randi([1 numvehicles],1,1);
    rj2=rj1;
    % Pick random job number 2
    while rj2==rj1
        %verifies that 2nd job is different from first
        rj2=randi([1 numvehicles],1,1);
    end
    % Check feasibility of swap
    if vehicle(rj1).ArrivalTime<=vehicle(rj2).ScheduledStart && ...
            vehicle(rj2).ArrivalTime<=vehicle(rj1).ScheduledStart
        % Make swap
        job1=vehicle(rj1);% temp. store job info to make swap easier
        job2=vehicle(rj2);
```

```
            vehicle(rj1).ScheduledMachine=job2.ScheduledMachine;
            vehicle(rj1).JobNumber=job2.JobNumber;
            vehicle(rj2).ScheduledMachine=job1.ScheduledMachine;
            vehicle(rj2).JobNumber=job1.JobNumber;
            vehicle(rj1).ScheduledStart=job2.ScheduledStart;
            vehicle(rj2).ScheduledStart=job1.ScheduledStart;

            % Adjust affected jobs
            for k=1:numvehicles
                % Find jobs on machine after swapped job
                if vehicle(k).ScheduledMachine==...
                        vehicle(rj1).ScheduledMachine && ...
                        vehicle(k).JobNumber>vehicle(rj1).JobNumber
                    vehicle(k).ScheduledStart=...
                        max(vehicle(k).ArrivalTime, ...
                        vehicle(k).ScheduledStart-...
                        (vehicle(rj2).ProcessingTime-...
                        vehicle(rj1).ProcessingTime));
                end
            end
            for k=1:numvehicles
                % Find jobs on machine after swapped job
                if vehicle(k).ScheduledMachine==...
                        vehicle(rj2).ScheduledMachine && ...
                        vehicle(k).JobNumber>vehicle(rj2).JobNumber
                    vehicle(k).ScheduledStart=...
                        max(vehicle(k).ArrivalTime, ...
```

```
                    vehicle(k).ScheduledStart-...
                    (vehicle(rj1).ProcessingTime-...
                    vehicle(rj2).ProcessingTime));
            end
        end

        vehicleNoDemand=vehicle;

        % Add demand interval delays back in
        for i=1:96
            if machinesavail(i)~=nummachines
                numberdown=nummachines-machinesavail(i);
                % Pick numberdown machines to pause charging
                % for 1 demand interval (15 minutes)
                % Look at which jobs currently scheduled during that
                % demand interval and see which will be completed
                % first and add 15 minutes to it.
                for j=1:numberdown
                    mintimerem=24;
                    for k=1:numvehicles
                        if vehicle(k).ScheduledStart<=(i/4) && ...
                                vehicle(k).ScheduledStart+...
                                vehicle(k).ProcessingTime>=(i/4)
                            % check to see if job falls in window
                            if vehicle(k).ScheduledStart+...
                                    vehicle(k).ProcessingTime-...
                                    (i/4)<=mintimerem
```

```
            %Find job with least time remaining
            mintimerem=...
                vehicle(k).ScheduledStart+...
                vehicle(k).ProcessingTime-(i/4);
            vehicletodelay=k;
            %keep track of job with least time rem.
        end
    end
end

%Update proc. times and props. on affected vehicle
vehicle(vehicletodelay).ProcessingTime=...
    vehicle(vehicletodelay).ProcessingTime+0.25;
vehicle(vehicletodelay).DemandDelays=...
    vehicle(vehicletodelay).DemandDelays+1;
TotalIntervalsDelayed=TotalIntervalsDelayed+1;
machinenum=vehicle(vehicletodelay).ScheduledMachine;
jobnum=vehicle(vehicletodelay).JobNumber;

%Delay sched. start for later jobs on affected machine
for k=1:numvehicles
    if vehicle(k).ScheduledMachine==...
            machinenum && vehicle(k).JobNumber>...
            jobnum
        vehicle(k).ScheduledStart=...
            vehicle(k).ScheduledStart+.25;
    end
```

```
                end
            end
        end
    end

    % Determine whether or not to keep the change

    % Calculate T
    T=T0*exp(alpha*n);
    %T=(T0/Tn)^(n/instances);

    LatestChargeStoppedNew=max([vehicle.ScheduledStart]+...
        [vehicle.ProcessingTime]);
    if LatestChargeStoppedNew<=LatestChargeStopped
        %Keep Change
        numswaps=numswaps+1;
        LatestChargeStopped=LatestChargeStoppedNew;
        ebest=LatestChargeStopped;
        vehiclefinal=vehicle;
        vehicle=vehicleNoDemand;
    elseif exp(-(LatestChargeStoppedNew-...
            LatestChargeStopped)/T)>rand(1)
        % Keep Change
        numswaps=numswaps+1;
        LatestChargeStopped=LatestChargeStoppedNew;
        ebest=LatestChargeStopped;
        vehiclefinal=vehicle;
```

```
                vehicle=vehicleNoDemand;
                numkeep=numkeep+1;
            else
                % Discard changes
                vehicle=vehiclebackup;
                clear vehicleNoDemand;
            end

        end
        n=n+1;
    end
    %vehiclefinal=vehicle;
    %disp(['The total number of job swaps: ', num2str(numswaps)])
    ChargeNotComp=0;
    for i=1:numvehicles
        if vehicle(i).ScheduledStart+vehicle(i).ProcessingTime>...
                vehicle(i).DesiredCompletion
            ChargeNotComp=ChargeNotComp+1;
        end
    end

    vehicle=vehiclefinal;

    if numkeep==0
        ebest=max([vehicle.ScheduledStart]+[vehicle.ProcessingTime]);
    end

```

```
    %ebest=max([vehicle.ScheduledStart]+[vehicle.ProcessingTime]);
    %disp(['The total makespan is: ', num2str(ebest-vehicle(1).ArrivalTime)])

    Results{16,index+offset}=ebest-vehicle(1).ArrivalTime; %makespan
    Results{17,index+offset}=vehicle;
    time(8,index+offset)=toc;
end
end
```

# APPENDICES V

## Serial Communication with Matlab m-file

```
%The following commands print a hex command to the serial port

%Assumed Station address of C9 in this example
getstat = hex2dec({'02','C9','08','00','31','C9','39','13'});
getpower = hex2dec({'02','C9','08','00','38','C9','40','13'});
heartbeat = hex2dec({'02','C9','08','00','15','C9','1D','13'});
chargeenable = hex2dec({'02','C9','08','00','10','C9','18','13'});
chargeauth = hex2dec({'02','C9','08','00','57','C9','5F','13'});
chargedisable = hex2dec({'02','C9','08','00','11','C9','19','13'});

if exist ('s') % variable 's' used to define serial port
    fclose (s)
    delete (s)
    clear s
end

% Get Status or heartbeat request
s = serial ('COM7');
set(s,'BaudRate',9600);
set(s,'InputBufferSize',10);
```

```
fopen (s)
s.RecordMode = 'index';
s.RecordDetail = 'verbose';
s.RecordName = 'serialLog.txt';
s.Timeout=1;
record(s)
% replace 'getstat' in following line with 'heartbeat' to request heartbeat
fwrite(s,getstat);
status = dec2hex(fread(s));
fclose(s)

% Get Power Reading request
s = serial ('COM7');
set(s,'BaudRate',9600);
set(s,'InputBufferSize',12);
fopen (s)
s.RecordMode = 'index';
s.RecordDetail = 'verbose';
s.RecordName = 'serialLog.txt';
s.Timeout=1;
record(s)
fwrite(s,getpower);
data = dec2hex(fread(s));
power=typecast(uint32(hex2dec([data(9,:),data(8,:),data(7,:),...
    data(6,:)])),'single'); %Conversion
fclose(s)

```

```
% Charge Enable / Disable / Authorize Command
s = serial ('COM7');
set(s,'BaudRate',9600);
set(s,'InputBufferSize',10);
fopen (s)
s.RecordMode = 'index';
s.RecordDetail = 'verbose';
s.RecordName = 'serialLog.txt';
s.Timeout=1;
record(s)
% replace 'chargedisable' in following line with 'chargeenable' or
% 'chargeauth' to send other commands.
fwrite(s,chargedisable);
fclose(s)
```

# CURRICULUM VITA

NICHOLAS FRANCIS JEWELL

1042 Lakeside Drive
Taylorsville, Kentucky 40071
Nicholas.Jewell@louisville.edu

## EDUCATION

University of Louisville, J.B. Speed School of Engineering
Ph.D. in Electrical Engineering — 2010-2014

University of Louisville, J.B. Speed School of Engineering
M. Eng. In Electrical and Computer Engineering — 2009-2010

University of Louisville, J.B. Speed School of Engineering
B.S. in Electrical and Computer Engineering — 2005-2009

## AWARDS

| | |
|---|---|
| Graduate Fellowship (Doctoral Degree), University of Louisville | 2010 |
| Trustees Scholar – President's Scholarship, University of Louisville | 2005 |
| Samuel T. Fife Scholarship, J.B. Speed School | 2008 |
| Theobald Scholarship, J.B. Speed School | 2008 |
| Deans Scholar, J.B. Speed School | Multiple Years |

## TEACHING EXPERIENCE

University of Louisville
Instructor (ECE654 "Advanced Data Networks") — 2014
Taught networking course at UofL and General
Electric Appliance Park.

Instructor (ECE322 "Intro. To ECE Computing Tools) — 2013
Taught course based on Matlab software suite.

Graduate Teaching Assistant (ECE320, ECE510, ECE533) 2009-2014
Graded assignments, provided tutoring, managed laboratories.

Lab Assistant (ECE518 and EE654) 2010
Assisted in lab setup / preparation by installing and configuring networking equipment. Developed various user manuals describing steps required and techniques needed to set up equipment for future courses.

## RELATED EXPERIENCE

Daktronics, Louisville, KY
Field Engineer / Event Support Technician 2010 – 2014
Troubleshoot and repair large format LED video displays and scoreboards. Diagnose and repair IPTV systems.

Office Computing Inc., Louisville, KY
Network and Computer Technician 1999 – 2014
Design and implement computer, phone, and CCTV networks for businesses and schools. Assemble new PCs and servers, and diagnose and troubleshoot PC problems.

E.I. DuPont de Nemours & Co. – Fluoroproducts Division, Louisville, KY
Electrical Engineering Co-op 2007 – 2009
Provided engineering support for design and maintenance of power distribution systems, instrumentation and control systems, and process hazard analyses.

## PUBLICATIONS AND PAPERS

*Analysis of Electric Vehicle Charge Scheduling and Effects on Electricity Demand Costs*
Journal Article, Energy Systems, Springer Berlin Heidelberg.
Presented at Systems & Optimization Aspects of Smart Grid
Challenges 2013, Tuscon, AZ. 2013

*A Power Monitoring and Control System to Minimize Electricity Demand Costs Associated with Electric Vehicle Charging Stations*
2012 IEEE International Electric Vehicle Conference, IEVC 2012. 2012

*Analysis of Forecasting Algorithms for Minimization of Electric Demand Costs for Electric Vehicle Charging in Commercial and Industrial Environments*
2012 IEEE Transportation Electrification Conference and Expo,
ITEC 2012. 2012

Patent Disclosure Filed
Power Monitoring and Control System for Electric Vehicle
Charging 2012

## MEMBERSHIPS

Institute of Electrical and Electronics Engineers (IEEE)
Tau Beta Pi Engineering Honor Society