

THESIS

ENERGY MANAGEMENT OF A UNIVERSITY CAMPUS UTILIZING SHORT-TERM LOAD
FORECASTING WITH AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT

ENERGY MANAGEMENT OF A UNIVERSITY CAMPUS UTILIZING SHORT-TERM LOAD FORECASTING WITH AN ARTIFICIAL NEURAL NETWORK

Electrical load forecasting is a tool that has been utilized by distribution designers and operators as a means for resource planning and generation dispatch. The techniques employed in these predictions are proving useful in the growing market of consumer, or end-user, participation in electrical energy consumption. These predictions are based on exogenous variables, such as weather, and time variables, such as day of week and time of day as well as prior energy consumption patterns. The participation of the end-user is a cornerstone of the Smart Grid initiative presented in the Energy Independence and Security Act of 2007, and is being made possible by the emergence of enabling technologies such as advanced metering infrastructure. The optimal application of the data provided by an advanced metering infrastructure is the primary motivation for the work done in this thesis. The methodology for using this data in an energy management scheme that utilizes a short-term load forecast is presented. The objective of this research is to quantify opportunities for a range of energy management and operation cost savings of a university campus through the use of a forecasted daily electrical load profile. The proposed algorithm for short-term load forecasting is optimized for Colorado State University's main campus, and utilizes an artificial neural network that accepts weather and time variables as inputs. The performance of the predicted daily electrical load is evaluated using a number of error measurements that seek to quantify the best application of the forecast. The energy management presented utilizes historical electrical load data from the local service provider to optimize the time of day that electrical loads are being managed.

Finally, the utilization of forecasts in the presented energy management scenario is evaluated based on cost and energy savings.

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NOMENCLATURE

Σ	Sum
AE	Austin Energy
AMI	Advanced metering infrastructure
ANN	Artificial neural network
APEL	Advanced Power Engineering Lab
ASME	American Society of Mechanical Engineers
B	Both feeders
CP	Critical peak
CPP	Critical peak pricing
CPS	Cyber physical system
CSU	Colorado State University
DG	Distributed generation
d_m	Sum of the error derivatives
d'_m	Sum of the error of the second derivatives
DOE	Department of Energy
DR	Demand response
DSM	Demand-side management
EECL	Engines and Energy Conversion Lab
EIS	Energy information system
EM	Energy management
e^λ	Conditioning variable for weight adjustments
F	1xn set of forecast values
f	Output of the ANN
FCU	Fort Collins Utility
FERC	Federal Electrical Regulatory Commission
FP	Facility peak
GS-750	General service 750
HVAC	Heating, ventilation, and air conditioning
kW	Kilowatt
kWh	Kilowatt-hour
LM	Levenberg-Marquardt
m	Epoch number
MAPE	Mean average percent error
MLP	Multilayer perceptron
MPE	Maximum percent error
MSE	Mean squared error
n	Number of points being forecast
N	Number of training patterns

NARX	Nonlinear autoregressive with exogenous inputs
NSF	National Science Foundation
PG&E	Pacific Gas and Electric
PRPA	Platte River Power Authority
RDSI	Renewable and Distributed Systems Integration
RTP	Real time pricing
SGI	Smart Grid initiative
STLF	Short-term load forecasting
T	1xn set of target values
t	Time
t_i	Target output for ith input pattern
T_{max}	Target value occurring at maximum error hour
T&G	Transmission and generation
ToU	Time of use
u	Input to logistic function
VFD	Variable frequency drive
w_1	Weight to hidden layer
w_2	Weight to output layer
w_m	Weights in epoch m
xi	Inputs to the ANN
y	Predicted value of ANN
y_o	Value to output layer
Δw_m	Change in weights between epochs
σ	Activation function
1	Feeder one – 299 kW
4	Feeder four – 100 kW

Chapter 1

INTRODUCTION

1.1 Objective

The objective of this research is to quantify opportunities for a range of energy management (EM) and operation cost savings at a university campus through the use of a forecasted daily electrical load profile. The application of a forecasting algorithm provides an option for anticipatory actions by the end-user to alter their electricity use based on a determined set of goals. The determination of the goals is based around the local rate structure available from the electricity service provider in an effort to simulate a likely scenario of savings.

1.2 Motivation

The combination of an aging electrical infrastructure and a strong incentive to transform the landscape of energy generation in the United States are the primary motivations for creating a power system that is more efficient and dynamic. The relatively small amount of capital investment in the electrical infrastructure has led to concerns about the ability of the industry to meet future needs [2]. The United States Department of Energy (DOE) has concluded that, “America’s electric system... is aging, inefficient, and congested, and incapable of meeting the future energy needs of the Information Economy without operational changes and substantial capital investment over the next several decades” [2]. This investment is largely in the form of increased communication between the consumption and generation sides of the electricity industry. A substantial part of this initiative is in the demonstration and deployment of an advanced metering infrastructure (AMI) that can provide real-time information to the end-user as

well as the generators and distribution entities. This dispersion of information technologies is expected to provide greater control and understanding of energy consumption to the larger players in the system (transmission, distribution, and generation) as well as to the end-users [3].

The AMI that is critical to the modernization of the electric industry relies heavily on the advancement and dispersion of the cyber-physical systems (CPS) present in the grid. CPS represents the interaction of computational and physical components. The National Science Foundation (NSF) sees the CPS of the future transforming “the way people interact with engineered systems, just as the Internet transformed the way people interact with information” [4]. The CPS created by an AMI provides large amounts of information about the operation of the electrical system, which creates a potential for a more involved management of the assets that constitute the electrical grid. The research proposed in this work seeks to use that information for a more efficient use of electrical energy on a university campus.

1.3 Scope

The scope of this thesis covers an electrical load forecasting technique that uses weather and time variables, as well as prior energy consumption patterns to predict power consumption 24 hours in advance. The forecasts are used to simulate an operation scheme that involves electrical load management on the main campus of CSU. The performance of the artificial neural network (ANN) used for this forecast is measured using four error metrics that help to fully quantify its usefulness in EM. These metrics are: mean average percent error (MAPE), maximum percent error (MPE), energy difference, and error in peak hour prediction. These four metrics provide a good indication of how the forecast might be used for varying management schemes, such as peak shaving or energy savings.

The EM approach proposed in this thesis is based around the projected electric power rate structures that FCU will be using for their larger industrial clients in the coming years [5]. A significant portion of CSUs bill is driven by CSUs electrical load during the hour when the generating utility, Platte River Power Authority (PRPA), experiences its power peak each month. EM is found to be most cost effective when performed around these “coincident peak” (CP) hours, therefore the energy savings scenarios are focused around those projected times.

This thesis does not cover the control strategies that would be essential to the implementation of these scenarios, but focuses on the opportunities for energy and cost savings for the actuators already in place.

1.4 Literature Search

The literature search for this thesis outlines the two main contributions of this thesis; forecasting and energy savings, as well as gives a broader perspective on demand-side management (DSM) in the context of the Smart Grid Initiative (SGI) of the government and the electric power industry. The following are the topics covered in the literature search:

- i. Smart Grid
- ii. Demand Side Management
- iii. Advanced Metering Infrastructure
- iv. Load Forecasting – Artificial Neural Network

1.4.1 Smart Grid

The Smart Grid, as outlined by the 110th US Congress, involves the proliferation of communication and information technologies in the generation, delivery, and consumption of electrical energy [6]. The motivation for the modernization of the electrical power grid is driven by the changing landscape of supply, such as renewable resources, as well as the increased stress on a grid that was developed decades ago. The advantages of a grid with greater communication

capabilities are improved reliability, security, and efficiency of the delivery and consumption of electric energy [7]. This improvement is achieved with flow of information and power in both directions, to and from the consumer, with the implementation of distributed generation (DG) and demand response (DR) technologies [6]. The aspect of the SGI addressed in this thesis focuses on the opportunities for changes in consumption based on the active participation of the end-user, or DSM.

1.4.2 Demand-Side Management and Demand Response

DSM is a term originally coined as “systematic utility and government activities designed to change the amount and/or timing of the customer’s use of electricity.” This research, however, also includes the possible activities of consumers in DSM [7]. The objective of a DSM program is to reduce the cost of electricity based on decreased capital costs to the utilities as well as introduces more control to the active consumer, via information. DR refers to a program in which the utility can control consumer demand remotely in response to activity on the grid. Many utilities across the US have DR programs, including a local service provider, Xcel energy, which offers credit on residential energy users bills for control of their central air conditioners [8].

The concepts of DSM and DR represent a shift in paradigm of end-user energy consumption. Changing the levels and timing of electricity demand at the customer end is an alternative to utilities investing in more capital infrastructure, as well as an opportunity for consumers to engage in active participation with utilities, i.e., decreased consumption for rebates [9]. Added advantages include increasing energy efficiency, lowering emissions, and prolonging availability of traditional energy supplies [10]. When well deployed, Smart Grid technologies engage the customer with the utility in decisions related to electricity consumption. This could potentially

lead to a more automated decision-making process for facilities and building energy managers at the end-user level. A basis for this knowledge is an AMI that provides the participants, i.e., the consumers and the utilities, information about electricity use. This is being done at many places around the country [11–13], and the world [14], [15], including CSU- the location of the case study presented in this thesis- where power quality meters for a subset of buildings are accessible over a secure internet site.

1.4.2.1 Advanced Metering Infrastructure

The communication networks of the current power grid are focused on the capital intensive equipment such as generation and transmission stations [16]. The proliferation of an AMI has the potential to automate processes such as: on-demand meter reading, time stamping of meter data, service connect/disconnect, control of customer assets, as well as other unforeseen uses [3], [16]. Momentum for the investment into advanced meters has been encouraged by a number of energy bills put forth by the US Congress in the last several years, including: the American and Recovery and Reinvestment Act of 2009, Energy Independence and Security Act of 2007, and the Energy Policy Act of 2005 [6], [17], [18]. A recent article in Wired magazine called smart meters the “lynchpin of the smart grid” and referred to them as one of the only emerging technologies of the new green-tech sector that is inevitable in the near future [19]. FERC estimated that by the end of 2010, the penetration of advanced meters was 13.4% in the US [20] with a projected 65 million meters to be deployed by the end of 2015 [21].

FCU is one of many utilities that have initiatives in place for advanced meters in their service area. FCU hopes to have 65,000 meters installed by the end of 2013, with an ensuing goal of a DR program to capitalize on this incoming information [22]. Some of the more ambitious initiatives in AMI deployment can be observed at Austin Energy (AE) and Pacific Gas and

Electric (PG&E). PG&E has a SmartMeterTM program that had close to 9 million advanced meters deployed by late 2011, with all customers in their service area expected to have the SmartMeterTM system installed by mid-2012 [11]. The benefits they expect from this rollout are more reliable service due to quicker notifications of outages, as well as customers becoming active participants in their energy usage [11]. AE is even farther along in their advanced meter program with the completion of all customer installations in 2009 [23].

1.4.3 Rate Structures

Another strong influence on DSM is the changing rate structures of retail electricity. The amount that customers should be charged is a complex problem because of the rapid changes in demand and the concomitant changes in transmission congestion and generation availability. Rate structures have been a topic of debate even back to the first days of commercially available electricity in the late 19th century when the idea of charging more for electricity during high loads of the system was an obvious choice to some engineers and economists [24]. Despite the early interest in marginal cost pricing, most of the US utility rate structures are in the nascent stages of time of day pricing. The most popular rate structure through the history of electricity has been a flat rate tariff, which is an average of the capital costs to the providers, as a function of the demand from the consumer [24]. This protects consumers from high fluctuations, but does not reflect the cost of supply at any given time. The next two sections cover some of the emerging rate structures beyond the flat-rate tariff that is still the norm for most consumers. Clearly, time of day rate structures necessitate deployment of an enabling technology such as AMI, and therefore both are expected to evolve together.

1.4.3.1 Time of Use Pricing

Deregulated electricity markets are emerging worldwide, incentivized by the theory that competitive markets lead to the lowest possible rates. Most of these deregulated markets end up as only a skeleton of a fully competitive environment to protect the consumers at the secondary distribution levels from the high fluctuations in electricity prices, although some utilities have offered this option to the secondary distribution level (residential) customers [25]. A popular alternative is time of use (ToU) pricing. In the ToU structure, the price is based on historical and forecasted demand for a blocked time of the day. Prices are then set for a period of the day, with the intent to incentivize lowered electricity consumption during the forecast peak usage time of the system.

Many utilities and regions are heading in the direction of ToU pricing [26–28]. One example of this is Portland General Electric, located in Portland, OR. They provide their residential customers with an opt-in program that entails three different prices throughout the day: on-peak (\$13.266¢/kWh), mid-peak (\$7.500¢/kWh), and off-peak (\$4.422¢/kWh). The hour designations for each price also changes depending on the season (i.e. winter or summer) [28]. Although this option is fairly simple, many ToU rate structures can be much more complex, given the constantly changing demand landscape. An example of this would be San Diego Gas and Electric, which has 6 different options for a residential ToU rate. Each rate structure has four possible prices depending on the energy used for the month and season [29].

Another form of ToU pricing that is widely used is critical peak pricing (CPP) [30], [31]. This often involves a signal sent to participating customers that is incentivized by reduced costs for that period. As opposed to ToU rates, CPP is aimed directly at reducing the peak over a longer time window, and is not in effect on a daily basis. A review of the impact of residential

programs with CPP on-peak demand found that it was plausible to expect a 30% reduction if CPP was used, but ToU could only expect 5% on-peak power (kW) reductions [32].

1.4.3.2 Real-time pricing

Real-time pricing (RTP) is an emerging cost structure in US utilities that closely reflects the supply/demand of bulk electricity and is seen by some economists as a necessity of an efficiently and comprehensively restructured electricity market [25], [33]. This proposed framework would be a direct reflection of the marginal cost of bulk electricity production passed onto the consumer. The implication of a RTP scheme is decreased demand during peaking times, which would be the expected response from consumers facing higher prices during high demand. Reference [34] presents a case study of residential customers that provides evidence for electricity in households to be significantly elastic, as well as an overall decrease in energy consumption in response to being exposed to RTP. Over 70 utilities in the United States have offered some form of RTP, with the majority of participants being large industrial customers [35].

1.4.3.3 Colorado State University Rates

CSUs main campus is serviced by FCU, which is a municipal distribution utility that serves all of the incorporated city of Fort Collins. FCU has a sole-source provider agreement with PRPA, which is a joint-action agency that was formed by the Colorado cities of Fort Collins, Longmont, Loveland, and Estes Park. The rate structures for customers of FCU are set by the Fort Collins City Council, and are designed to be revenue neutral since FCU is a nonprofit entity.

The rate structure for CSU is dictated by their designation as a general service 750 (GS-750) customer of FCU. There are three demand components to this rate structure: energy demand,

facility peak (FP), and CP. This thesis uses the published 2012 rates for the FCU service area [36]. The rate structures for the GS-750 customers beyond 2012 are not yet decided, but speculation suggests that they are not subject to drastic changes in the near future [5]. There are some components of a dynamic-pricing scheme in this rate structure that involve peak rebates and incentives, although these are subject to approval by the Executive Director of the utility. There is a seasonal component to the structure as well; the summer months of June, July, and August are subject to higher energy demand and CP charges, which will be explained in greater detail in section 3.1 [36].

There is also a charge to CSU FP demand. This involves a ratchet system that charges the customer for the maximum FP demand over the month billing period, which can be no less than the maximum monthly FP over the last eleven months. As a GS-750 customer, every kW over 750 kW is charged less than the charge for the first 750 kW [36].

1.4.4 Load Forecasting

Load forecasting is a necessary tool in DSM. Large electric distribution consumers, such as a university campus, have electricity bills that represent a considerable fraction of the entity's operating costs. Forecasting can help in determining where savings can be made, as well as uncover inefficiencies in the system. The opportunities for rescheduling certain loads could also be useful as enabling technologies such as energy storage are brought into the system. Short-term load forecasting (STLF) looks at forecasting load from a few minutes to a week ahead, and encompasses time spans that are pertinent to the DSM applications presented in this thesis.

1.4.4.1 State of the Art in Short-Term Load Forecasting

STLF has become one of the major areas of research in electrical power engineering because it is essential to the efficient operation of a power system. The electricity supply industry uses forecasting in a mode termed *off-line forecasting*, which refers to the scheduling of generating units based on expected demand. The accuracy of these forecasts is essential for the reliability of supply in large part due to the relatively large time constants of thermal generating units, which account for a large fraction of the generating capacity are the most prolific in the power supply industry [37], [38]. The electric power industry uses a technique termed *online forecasting* to ensure that load dispatching is within the operational parameters of the system [38], [39]. Load dispatching is performed a few hours in advance, and is therefore dependent on the accuracy of the forecasts in order to find the optimal generating mix to minimize the cost function [38], [40], [41]. Many techniques have been used in both online and offline forecasting, with most properly classified as statistical techniques, although the emergence of artificial intelligence technologies has expanded the options over the last decades. The restructuring and modernization of the electric power industry has also influenced the importance of forecasting, putting more pressure on the financial risks associated with poor predictions and potentially changing the way electricity is consumed [42].

The impetus to improve forecasting techniques, as well as the differences of economic and climatic variables between utilities incentivizes an active research area in STLF. The system load is influenced by a number of factors, including: economics, time, weather, and random effects [43]. One of the challenges associated with STLF is that these factors influence different areas in different ways and therefore require some specificity built into the prediction algorithms [44].

The following is an abridged list of STLF techniques used by the power industry, not including the multitude of variations and approaches to each method:

- i. Multiple Linear Regression
- ii. Stochastic Time Series
- iii. General Exponential Smoothing
- iv. State Space Methods
- v. Knowledge Based Approach
- vi. Kalman Filter
- vii. ANNs

The STLF performed in this thesis employs ANNs, which will be covered in greater detail in section 1.4.4.2. The following section will look at how some of the other techniques in the previous list have been applied.

1.4.4.1.1 *Applied Short-Term Load Forecasting Techniques*

The variability of electric power service areas and generation portfolios incentivizes the varying forecasting techniques, of which a few are examined in this section. An expert system-based algorithm for use in 1-to-24 hour load forecasting is presented by reference [45]. This is built largely on the relationships between weather and electrical load. Variables of interest in forecasting are identified by season, and the typical time variables of day of week and time of day are also utilized. This identification of impacting variables led to a rule-based forecasting technique that took time of day, season, and changes in weather over the period being forecast as the predictors. The algorithm produces 24 separate forecasts. This system is shown to be equally good, if not better, than the popular regression techniques used at the time.

Kalman filtering has also been a widely studied technique for STLF. Reference [46] proposes a technique that uses two stages for forecasting: first a mean is predicted, and second, a correction factor is calculated using real-time feedback of previous hour forecast errors. This

algorithm also incorporated a “fading memory” which causes data farther back in time to be less influential on the current forecast.

A regression based approach for one-day ahead forecasts is identified by reference [47]. The technique is developed for the Irish Electricity Supply Board as a tool in predicting the system load and generation expectation. The electrical load profile is divided into a ‘normal’ load and a weather sensitive load. The normal load is identified using historical weather variables and linear regression, and the weather sensitive load is estimated using parameters of regression analysis. This algorithm includes techniques for the selection of predictive variables and identification and treatment of influential points in the data. The following section will look closely at ANNs for STLF applications.

1.4.4.2 Artificial Neural Networks

ANNs have received an extensive share of the research attention in STLF since the late 1980’s. Hippert et al., in [48], explores the growth of ANNs in electrical load forecasting with particular focus on the variation in metrics to measure success. Reference [48] claims that the lack of any accepted standards for ANN reporting has led to skepticism within the power systems community, even though the ANNs often perform as well as, if not better than, the more standard models. The two main shortcomings in the associated literature has been a problem of over-fitting of the data and the lack of systematic testing of the ANN [48], [49].

The typical structure of ANNs in this area of research has 24 output nodes representing the 24 hourly loads of the day. Each of these hours has multiple inputs, which often includes historical data as well as weather and time variables. A number of statistical techniques as well as artificial intelligence have been combined with ANNs for pre and post-processing. The pre-processing of data is best analyzed by considering the most correlated variables, with the

calendar date being considered the most influential [48]. Separating the weekends from the weekdays is a popular method in pre-processing if load profiles are noticeably different [50]. Weather variables are the second most important factor affecting load profile. Reference [51] presents an in-depth look at which variables most affected the load profile, based on case studies on a realistic system, i.e., the Egyptian Unified System, by calculating linear correlation coefficients. Significant findings of [51] include the identification of historical load as the most influencing factor, while temperature is the most influential weather variable, especially in summer and fall.

Another challenge in ANN design is the decision on the complexity of the hidden layers [49], [52]. Extensive research has addressed this issue with a number of conclusions, but little agreement on a standardized method [48], [52]. The number of neurons in the hidden layer affects the complexity of the network, and in turn, the ability of the ANN to give an accurate forecast with out-of-sample data [48], [49]. In this thesis, a heuristic technique that looks at different numbers of neurons and associated statistics is employed for this purpose. The technique presented here also uses *early stopping*- a technique that employs a part of the data to test how well the network is generalizing. This is known as cross-validation, and is a widely used technique that may achieve good generalization even if the neural network is designed with too many parameters [48], [53].

1.4.5 Energy Information Systems

Energy information systems (EIS) collect and organize energy use information for use in building operation awareness, anomaly detection, and energy performance tracking [9], [54]. This technology often combines an AMI with data acquisition software and web-accessibility that allows for analysis of the whole-building electric data. Oftentimes the EIS will include

weather information, price signals, building system data, and energy demand response event details. Evidence shows that permanent metering and monitoring is a valuable tool in recognizing opportunities for improving the overall efficiency of a building [55]. The term for an EIS that operates and analyzes multiple buildings is referred to as Enterprise EM [56].

A thorough evaluation of EIS products and user case studies was performed in reference [54]. It was found that while the capabilities of most EIS systems can improve the energy performance of a building or group of buildings, the EIS is not commonly used to its full potential. Reference [50] pointed out that some organizations made concerted efforts to employ an EIS system to its full potential and saw very positive payoffs.

1.5 Computational tools

The programming language utilized in this thesis is Matlab[®], version R2011a. The ANN algorithm discussed in chapter 2, as well as the EM algorithm discussed in chapter 3 were created in the Matlab[®] environment utilizing native Matlab[®] programming and the *neural network toolbox*, an add-on to the core Matlab[®] system. The code for both algorithms is provided in Appendix A. The data set is available via the Engineering Network Services of CSU, T:\projects\CSUBEM (for access contact Prof. Siddharth Suryanarayanan or Prof. Daniel Zimmerle, CSU).

1.6 Organization of thesis

The focus of this thesis is on developing an EM scenario with the utilization of a load forecasting algorithm. Chapter 2 details the STLF ANN that is optimized for 24-hour ahead forecasts for use on CSUs main campus. Here, the network structure and methods of data management are explained in great detail, as well as the results of testing the network on out-of

sample data. Chapter 3 builds on the load forecasting developed in chapter 2 with an EM pattern of actions that are based on controllable assets on CSUs main campus. A scenario of the eventual implementation of the EM with utilization of the forecast is also presented in this chapter. Chapter 4 concludes the thesis with final thoughts and a discussion on possible future work.

Chapter 2

FORECASTING WITH AN ARTIFICIAL NEURAL NETWORK

This chapter presents the application and methodology of the forecasting algorithm employed for use on CSUs main campus. A significant portion of the chapter is devoted to explaining the conceptual framework of ANNs, the techniques used for optimizing the architecture of the ANN, as well as an overview of data management and processing that is necessary for acceptable and usable 24-hour forecasts. The performance of the forecasts is examined through a number of measures that attempt to quantify the applicability of the prediction to its eventual uses, as well as give a full picture of the capabilities of the forecasting algorithm. Prior to describing the ANN, it is pertinent to present some descriptive details of CSUs main campus, which is addressed in the following section. Section 2.3 also provides a brief summary of alternative techniques and exploratory data mining that was performed before deciding on ANNs as the forecasting algorithm.

2.1 Campus Information and Data

CSU is located in Fort Collins, Colorado (N40 34.39686 W105 5.274 [57]) and as of March 2012 has about 200 buildings spread over an area of roughly one square mile which is used to varying degrees by a population of approximately 30,000 enrolled students and 3850 faculty and staff members on the campus [58]. The average electrical load over the period considered in the case study is around eleven MW. The monthly climatic data for Fort Collins, CO is given in Figure 1.

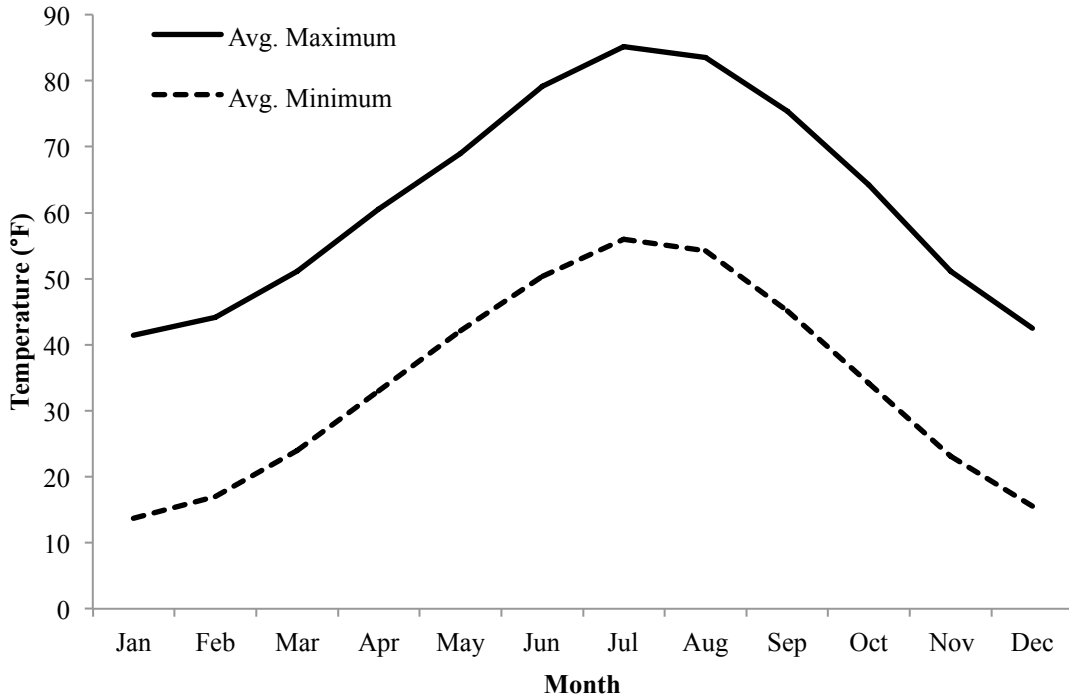


Figure 1. Monthly climatic data for Fort Collins, CO [59].

2.2 Power Data for Colorado State University

The electrical power data logged at the main campus of CSU, located in Fort Collins, is hourly, and spans the time period from June 2006 through December 2011, with weather variables collected for the same time period and at the same data granularity [60]. The network is tested on the last 242 available days in the dataset (all days in 2011 for which data is applicable for this case study). Daily forecasts are produced for the 24-hour period starting at one A.M. The start and end times are somewhat arbitrary and could be changed in an EM system to reflect the most efficient time of day to train the network, although the accuracy of the forecasts could be effected by this change. The ANN is structured for data nearer in time to the prediction date to be more influential to the forecast. This time-series technique allows for growth and changes in

consumption patterns over the five-year period to be accounted for by the network, which will be addressed in greater detail in the following sections.

2.3 *Preliminary Data Analysis*

Regression is a technique employed in exploring a simple explanation for the relationship between weather variables and power consumption on CSUs campus. Figure 2 shows the relationship between the independent variable of outside temperature and the dependent variable of power for all available data in 2010. Determination of the relationship between variables in STLF has traditionally separated datasets by season and/or day in order to find a relationship that can provide accurate predictions of the independent variable, power [39], [61]. Dividing the dataset by season results in Figure 3 and 4, which are the regression of temperature and power for summer and winter months. The reason for this seasonal division is that the summer months of June, July, and August often exhibit a load profile that is distinctive to those three months. The coefficient of determination R^2 for the months in Figure 3 is 0.66, and 0.58 for Figure 4. Relationships between the variables of Figures 2-4 are similar to all five years of available data.

The results of simple linear regression being applied to temperature-power relationships show no clear correlation or predictive capability between these variables. It is plausible that there are significant relationships given a particular pre-processing routine, but due to the application of the forecasting algorithm, it is a priority to keep the pre-processing to a minimum. End-user participation in forecasting requires a level of simplicity that is not easily achieved in relationship analysis beyond the level attempted in this section. The simplistic application of ANNs in forecasting is one of the primary reasons for utilizing the proposed algorithm of this chapter. Other reasons include the strong research interest in ANNs in recent years [38] and the

proven ability to predict electrical load as well if not better than other techniques [52], [62], [63].

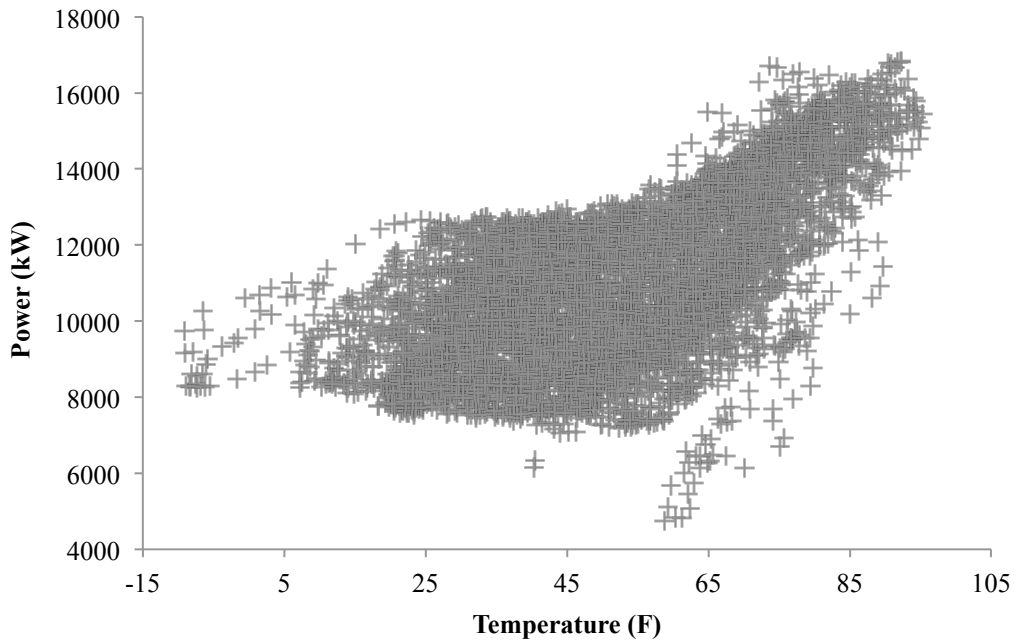


Figure 2. Regression of power consumption as a function of temperature for the all weekdays in 2010.

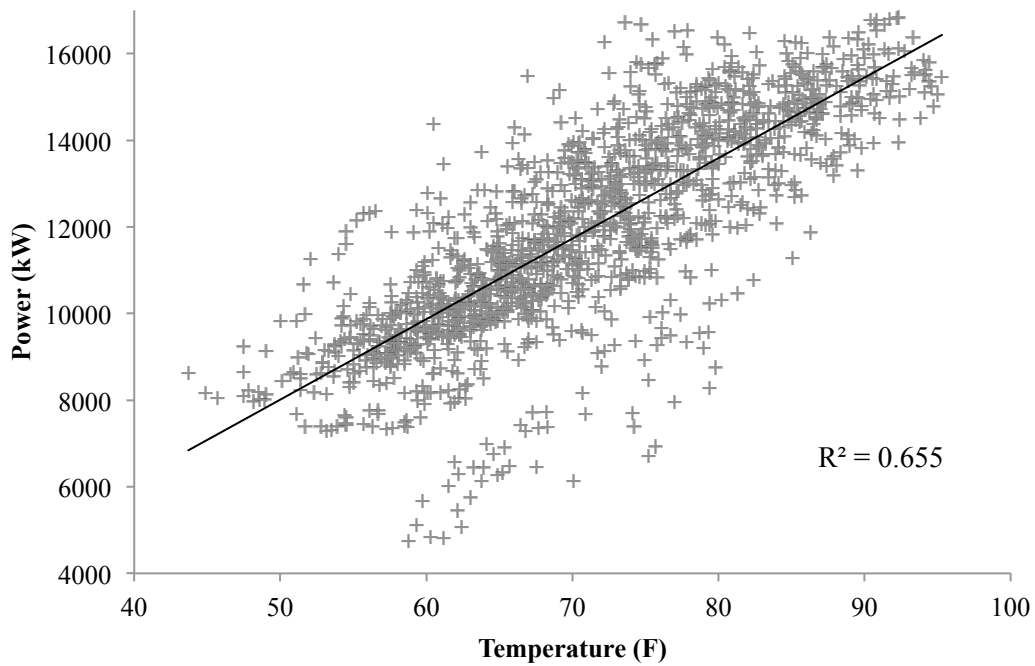


Figure 3. Regression of power consumption as a function of temperature for the months of June through August of 2010.

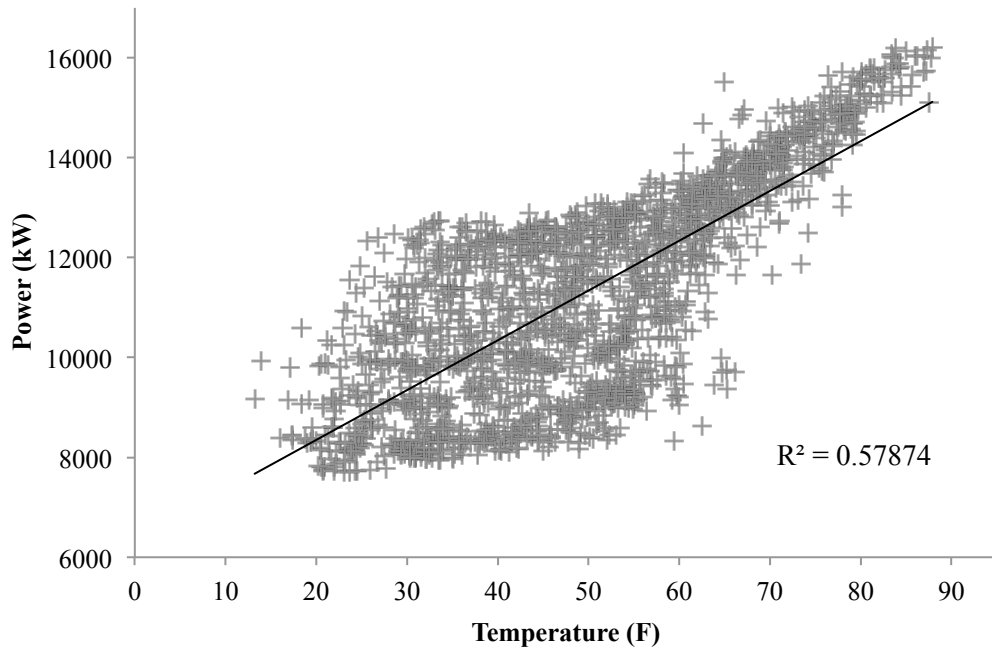


Figure 4. Regression of power consumption as a function of temperature for the months of September through December of 2010.

2.4 Artificial Neural Network

ANNs perform computations to mimic the learning processes of the human brain, which consists of a parallel-distributed structure of neurons that uses the *learned knowledge* to match inputs to outputs and make the “map” of the inputs to outputs available for use [53]. Neurons, the primary computing units of the ANN, are modeled after their namesakes in the brain, and are developed in a way that allows *plasticity*, or the ability to adapt to changes in the environment. The diversity in ANN models stems from a lack of understanding the mechanism of neural information processing in the brain, and the subsequent experimentation to attempt to imitate those processes [53], [64]. The next section provides an overview of ANN models that have been developed for time-series forecasting, in which memory is embedded in the model.

2.4.1 Forecasting with Artificial Neural Networks

The multilayer perceptron (MLP) is one of the most well-known ANN architectures for prediction algorithms, and is popular because of its flexibility in assuming shapes of complex patterns [64]. MLPs consist of three layers: the input layer, the hidden layer, and the output layer. A diagram of the basic architecture of a MLP ANN is shown in Figure 5. The input layer is the part of the network that is ‘sensing’ the outside world, represented in Figure 5 as $x_1 \dots x_n$.

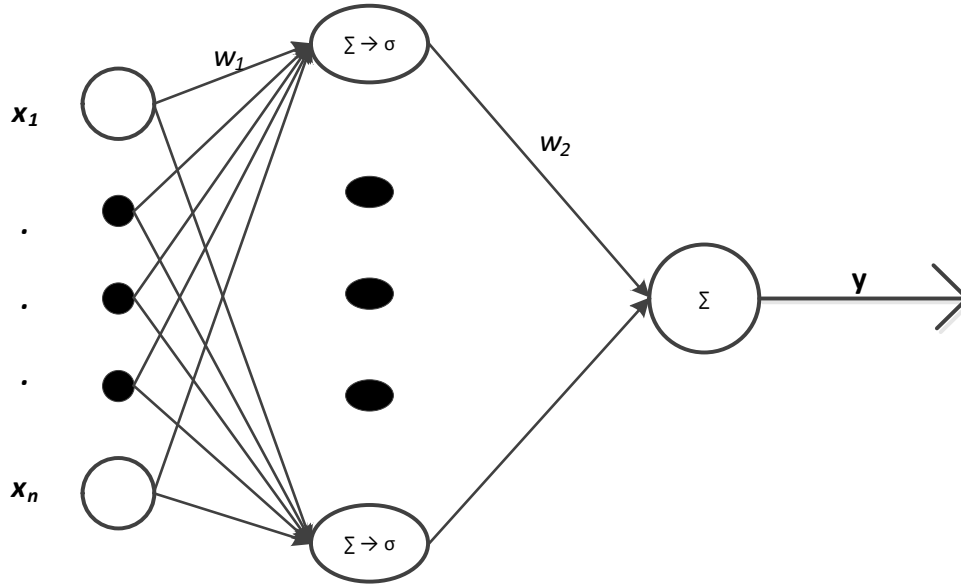


Figure 5. Configuration of multilayer perceptron neural network.

The neurons on the input layer are often sensing weather, time variables, and historical power data in STLF applications [52], [63], [65]. The middle, or hidden, layer is not connected to the external inputs directly, but is connected through weighted inputs, represented by the arrows labeled w_1 . The hidden layer processes the weighted inputs by first summing them and then passing those values through a nonlinear transfer function, denoted by σ . The purpose of the transfer function is to shift the inputs from simple linear to complex nonlinear domains, allowing the ANN to map nonlinear relationships between input and output. The number of hidden layers

is most often one, although the decision mechanism for the number of neurons in this layer is not well established [48]. It is often determined through heuristic techniques specific to the application. The values computed by the hidden layer are connected to the output layer with weighted inputs, w_2 . These are summed at the output layer to compute a final value or values, depending on the ANN architecture.

The process of learning, or training, by the MLP requires a historical dataset that has matching inputs and outputs. Learning consists of presenting the network with an input vector, passing them through the hidden and output layer, and measuring how well the ANNs predicted value matches the expected value. The absolute value of this error is then compared to an acceptable threshold, and if the error is too large, the information is back-propagated through the network to make adjustments. The weights of the hidden layer, w_1 , and the output layer, w_2 , are adjusted until an acceptable level of error is computed. Therefore, each neuron in the output layer of a MLP is designed to compute two things: the output signal, which is a function of the weighted inputs to the neuron, and the error between the output signal and the desired output. The computation of this error can take many forms and merits further discussion, which will be covered in section 2.4.5, which explains some of the specifics of the ANN proposed in this thesis.

2.4.2 Pre-processing of Data

Processing of data is performed prior to training to improve the forecasts as well as focus the predictions on the days where load profile manipulation is most effective in offsetting costs and improving efficiency. CSU has a distinct weekday profile that is different from the weekend, as illustrated in Figure 6. This thesis considers weekdays, designated ‘occupied days,’ to be more important than weekends in load profile management; hence, the efforts are focused on

forecasting the hourly electrical energy consumption for the ‘occupied days’. University holidays have a similar profile to the weekends, and are therefore part of an excluded set. Training the networks with only occupied days improves the performance of the prediction, although the distinction of occupied days is a subjective consideration given the nature of a campus that has varying degrees of activity. Standard semester breaks are considered

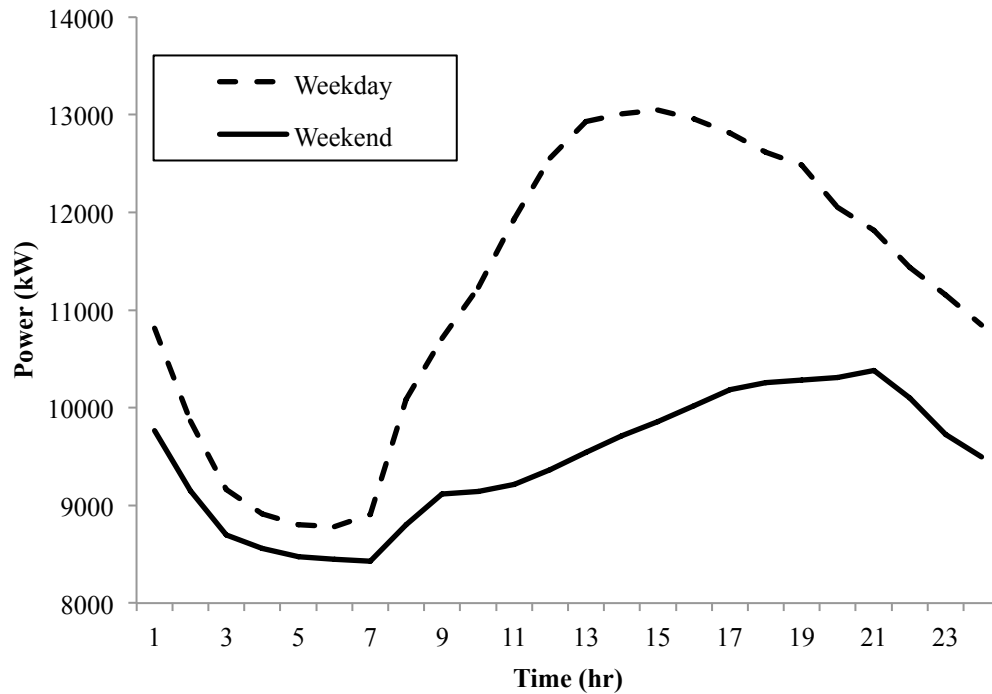


Figure 6. Typical weekday and typical weekend electrical load profiles for CSUs main campus.

‘unoccupied,’ excepting winter break, which is observed to have enough activity over most of it to be included in the dataset for training and prediction. Another exclusion from training was an outlier created by a power outage event in Fort Collins.

The reason for excluding the power outage event is justified by a four-nines ($N_9=3.9$) reliability of electricity supply available to the campus [66]. The outlier day, February 1st, 2011, was replaced in the dataset with the load profile of the day after, February 2nd, so that the day

would not be left out of the prediction test set. This replacement technique is chosen somewhat subjectively given the inability of the ANN to predict such behavior, and the desire to keep training for the subsequent days based off of normal, predictable, behavior.

Once the data has been processed to include only the occupied days, the dataset is divided into a training set and a validation set. The network described in this thesis uses 75% of the data for training and the remaining 25% for validation. The purpose of a validation set is to avoid over-fitting of the data, which will decrease the generalization capabilities of the network causing poor predictions. The validation set is used as a test of the ANN every few iterations and will stop the training, commonly referred to as *early-stopping*, if over-fitting occurs. The specifics of training and validation are explained in detail in section 2.4.5.

Another step in pre-processing is the normalization of the data before being used for the training phase. Here, the minimum and maximum values of each category are normalized to [-1 1]. Some type of normalization is standard practice before applying the inputs to the network, as shown in [67], so that particular inputs are not overly influential because of the scale on which they are measured. An example of a day of exogenous inputs to the network is shown in table 1.

2.4.3 Simulation of Real-Time Forecasts

The process used for forecasting daily electrical load profiles is as follows:

- 1) Choose a day in 2011 (all available days in 2011 is the test set)
- 2) Train the ANN on *all* previous input variables and corresponding outputs (all available data *up to* midnight of the day to be predicted)
- 3) Apply inputs for predicted day to the ANN
- 4) Compare forecast to actual electrical load profile for day with varying error measures.

The *actual* weather data logged at the Fort Collins Weather Station [60] for the test day is used in the network for modeling weather-related variables, although in practice these variables could be

based on forecasts. Reference [68] looks at how weather forecasting accuracy can affect the quality of the electrical load prediction, which is a possible avenue for continued research in this specific application.

Table 1. Example of exogenous inputs to ANN.

Solar irradiance (W/m ²)	Temperature (°F)	Relative humidity (%)	Wind speed (mph)	Day of week (1-7)	Hour of day *
0	66.7	66.8	3.3	2	0:00
0	65.6	69.5	3.3	2	1:00
0	64.9	72.4	1.5	2	2:00
0	64.2	75.5	1.9	2	3:00
0	64.3	74.6	2.6	2	4:00
2.3	64.3	76.8	2.7	2	5:00
46.3	64.1	77	1.4	2	6:00
212.1	65.4	75	3.3	2	7:00
411.3	67.4	71.4	4	2	8:00
650.1	71	63.9	2.3	2	9:00
805	73.6	58.4	2.6	2	10:00
912.1	76.6	51.3	3.3	2	11:00
879.6	78.5	48	5.5	2	12:00
326.1	77.2	48.7	6.1	2	13:00
263	76.6	48.2	5.8	2	14:00
293.1	77.4	46.2	3.9	2	15:00
276.1	68.5	61	4.6	2	16:00
548	72.1	52.8	3.6	2	17:00
300.3	72.6	48.9	4.5	2	18:00
118	71.3	51.2	3.1	2	19:00
6.2	68	60.3	5.6	2	20:00
0	67.1	68.3	6.9	2	21:00
0	66.9	68.5	5.3	2	22:00
0	66.5	69	3.6	2	23:00

* The actual input values for timescale are in a serial date number specific to Matlab®.

2.4.4 Network Structure

The ANN for STLTF for the main campus of CSU is a time-series forecaster that utilizes the sequence of inputs as informative to the prediction. Figure 7 shows the basic structure of the network. This is representative of a non-linear autoregressive with external inputs (NARx) ANN, which is a dynamically-driven recurrent network that consists of an input layer, a hidden layer, and an output layer. The choice of one hidden layer is a combination of historical success [48], and the desire to maintain the simplicity of the architecture, in accordance with Occam's razor, with acceptable predictions. The output power at time t is informed by inputs presented to the network with no delay, at time t , as well as with a one-hour delay, at time $(t-1)$, and a two-hour delay, at time $(t-2)$. The inputs that have a time delay associated with them are represented with a (3) below them in Figure 7, meaning there are three inputs to the one variable type. The autoregressive aspect of the network uses power output that is fed back through to the input layer with all 24 previous hours in the vector, i.e., hours 1-24 of the previous day informs the output of hour 1 of the current day, and so on. Figure 7 is simplified in that the delayed input neurons are not shown, which are represented below in an abbreviated version of the governing Equation (1) for the ANN implemented for forecasting CSUs main campus.

$$y(t) = f(temp(t), temp(t - 1), solar\ irradiance(t) \dots power(t - 24)) \quad (1)$$

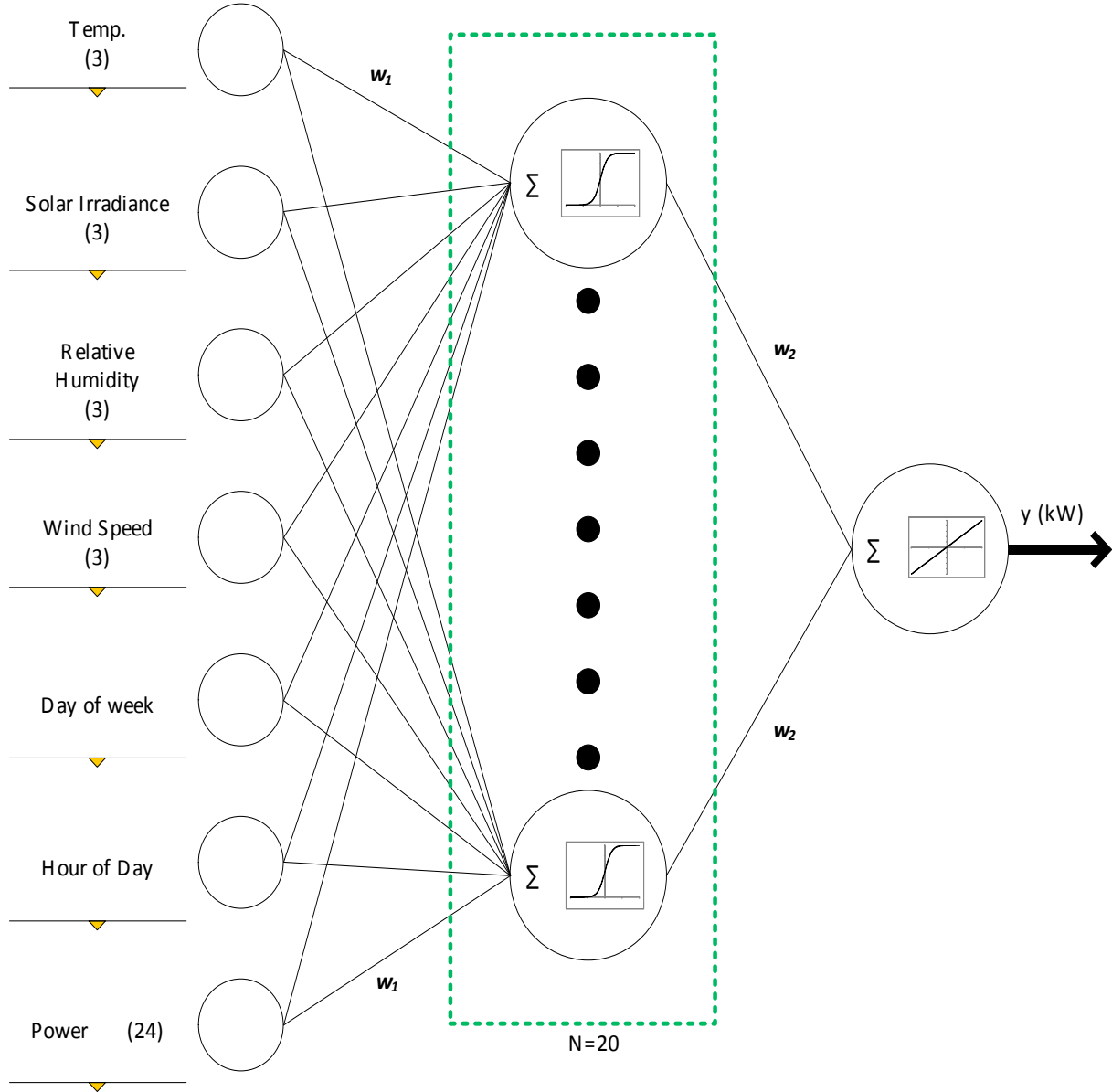


Figure 7. Architecture of ANN applied to CSU electrical load profile.

A recurrent network is a feed-forward, multilayer perceptron (MLP) network that attempts to build the autocorrelation structure of a series internally, essentially building a memory of how things are changing, which is used in the forecasting map [64]. This is especially important in the case presented in this paper because of the large period of time that the experimental dataset spans. The five-year period that is used for training involves many new building and energy-use

renovations as well as new structures on campus. MLP networks are flexible, which makes them a good choice when there is high complexity within the data [64]. The hidden layer contains nonlinear neurons that perform continuous, nonlinear transformations of the weighted inputs [64]. The transforming activation function employed here is the sigmoid logistic function, defined as,

$$y_0 = \frac{1}{1 + e^{-u}} \quad (2)$$

where u is the input, and y_0 is the value sent to the output layer, which is composed of a linear function.

2.4.5 Training the Network

Training consists of adjusting weights on the input layer and the output layer until the combination of weights and inputs creates an acceptable output. This is achieved by the Levenberg-Marquardt (LM) learning method, which is one of the most popular optimization methods and is often the most efficient at converging to the optimum weights [64]. It is a second-order method that combines the advantages of both the Gauss-Newton and steepest descent methods to minimize the error. The mean squared error (MSE) is the error that is to be minimized to achieve an acceptable output from the ANN. The MSE depicted as a function of the weights, w_m , is

$$MSE = \frac{1}{N} \sum_{i=1}^N [t_i - f(w_m, x_i)]^2 \quad (3)$$

where t_i is the target output for the i th input pattern, f is the output of the ANN, and a function of the w and x_i , the inputs, and N is the number of training patterns.

Second-order methods, such as LM, use both the slope and the curvature at the current point in weight space to speed up the convergence process [64]. LM is particularly dynamic because it adjusts the learning rate based on the proximity to the minimum value of the error gradient. The weights are adjusted in each epoch, m , as

$$\Delta w_m = -\frac{d_m}{d'_m + e^\lambda}. \quad (4)$$

where d_m is the sum of the error derivatives, with d'_m as the second derivative. The term e^λ produces a conditioning effect for the second derivative, and is adjusted automatically to improve the stability of the solution. When the MSE between two consecutive epochs is less than the minimum specified error, training stops. Training is also stopped as mentioned in section 2.4.2, if the validation checks conclude that over-fitting is occurring. Every few iterations, the ANN is given inputs from the validation set and run to see how well it can predict the output. If there are signs of not being able to generalize, or predict outputs outside of the training set within the acceptable error, then *early-stopping* occurs. This keeps the network from learning the specifics of the training too well.

2.4.6 Hidden Layer

The number of neurons in the hidden layer is an important aspect in designing the architecture of the ANN. There are many rules of thumb for choosing the number of neurons in the hidden layer, although there is no standardized method. It is often a subjective choice, which is exemplified in the extensive review of [48]. The approach presented here combines a measure of error on multiple test sets, as well as some subjectivity in the final decision. Observations of the prediction accuracy of the network with one to fifty neurons, on a single day as a test set, was

used to determine the number of hidden neurons. Each network size was run thirteen times in hopes of achieving a good average. Thirteen iterations were performed as a default because of the computational time constraints, but with the judgment that this was enough to justify a result. The number of hidden neurons is decided based on the variance of the predictions and the diminishing returns in the MAPE when another neuron is added.

2.5 Performance Metrics

There are a number of error measurements that are relevant for quantifying the performance of the model. The most widely reported error in neural network literature is the MAPE, given in (2),

$$MAPE = \frac{\sum \left(\frac{|\vec{F} - \vec{T}|}{\vec{T}} * 100 \right)}{n} \quad (5)$$

where \vec{F} is a $(1 \times n)$ set of forecast values, \vec{T} is a $(1 \times n)$ set of observed values, and n is the number of points being forecast, which in this case is 24. Three additional performance measures that are informative when looking at the forecasting accuracy are: 1) the maximum error throughout a 24-hour period (MPE, eq. 6); 2) the difference in total electric energy consumed over the 24-hour period (eq. 7), indicated by the area contained by the load profile curve (Figure 6) and, 3) the ability to predict the hour of the peak, termed ‘magnitude of peak hour.’

The MPE is the ratio of the largest residual to the target value (T_{max}) occurring at that hour. This metric quantifies the largest error for a day’s forecast as a percentage of the total load on the system. The values as well as the time of day that this error is most likely to occur are both informative measures of how and when this forecast tool is appropriate to use. The usefulness of this and other metrics will be discussed in greater detail in section 2.8.

$$MPE = \frac{|\vec{F} - \vec{T}|_{\infty}}{T_{max}} * 100. \quad (6)$$

The energy difference is the ratio of the difference in electric energy consumption corresponding to the forecast and the observed values to the electric energy consumed corresponding to the observed values, for a 24-hour period (eq. 7). This is provided as a percentage of the total energy consumed over the whole day.

$$Energy\ difference = \frac{\int_0^{n-1} \vec{F} - \int_0^{n-1} \vec{T}}{\int_0^{n-1} \vec{T}} * 100. \quad (7)$$

2.6 Forecast Load Profile

The forecast load profile is given as an average of a set of three load profiles output by the ANN for a given data input set. This is done in an attempt to minimize the random effects of the initialization of the weights. The test sets are 24-hour periods that are out-of-sample sets of data, meaning that the network has never been exposed to the day that is predicted. The training and validation sets are comprised of all the data available previous to the forecast day. In this case study, analyses corresponding to 242 separate forecast days, all of which are in 2011, are presented in the following section.

2.7 Results

The results of both the final network architecture and the performance of the forecasts are presented in the following section.

2.7.1 *Hidden Layer Size*

Figures 8 and 9 shows the results of the hidden layer test runs. Each boxplot represents thirteen separate predictions on the same test day. The variability comes from the initialization of weights and biases. There is a decrease in the error as more neurons are added, although judgment is exercised to decide on the point of diminishing return when adding another neuron. It is observed in Figure 9 that there is a relatively small variance (0.33) no outliers, and low error (MAPE=1.74) around twenty neurons; hence, this is incorporated in the ANN architecture.

It is worth noting that this test is heuristic and only applied to one day (February 9th, 2011), and is therefore not assured to be the optimal solution for all test days. Further analysis was applied to the relatively ‘good’ results found at one neuron to explore the possibility of this simple solution. When a one-neuron network was subject to other random test days, it performed poorly compared to the average errors found over the test set, such as the load profiles shown in Figure 10.

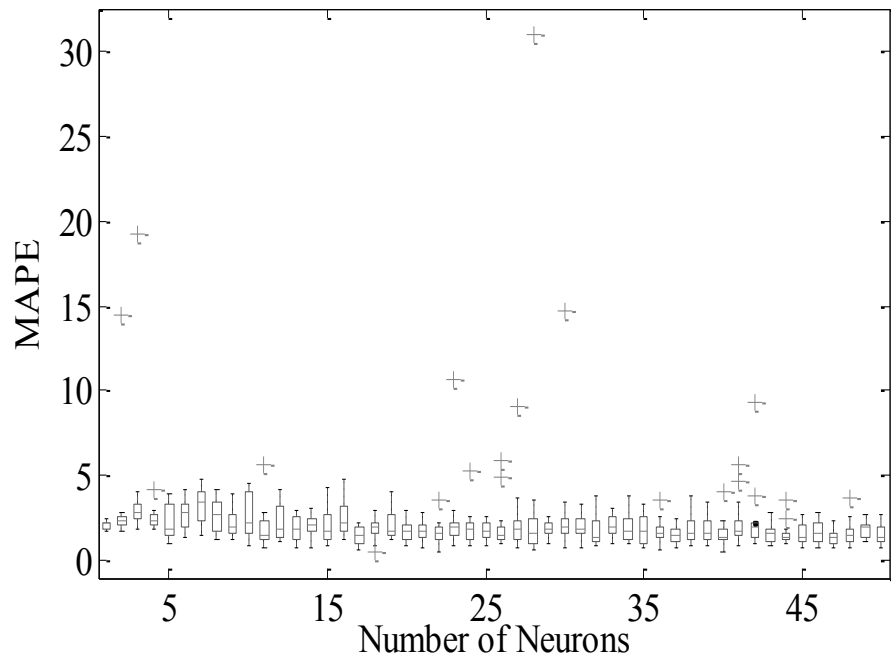


Figure 8. MAPE versus number of neurons in the hidden layer of the ANN.

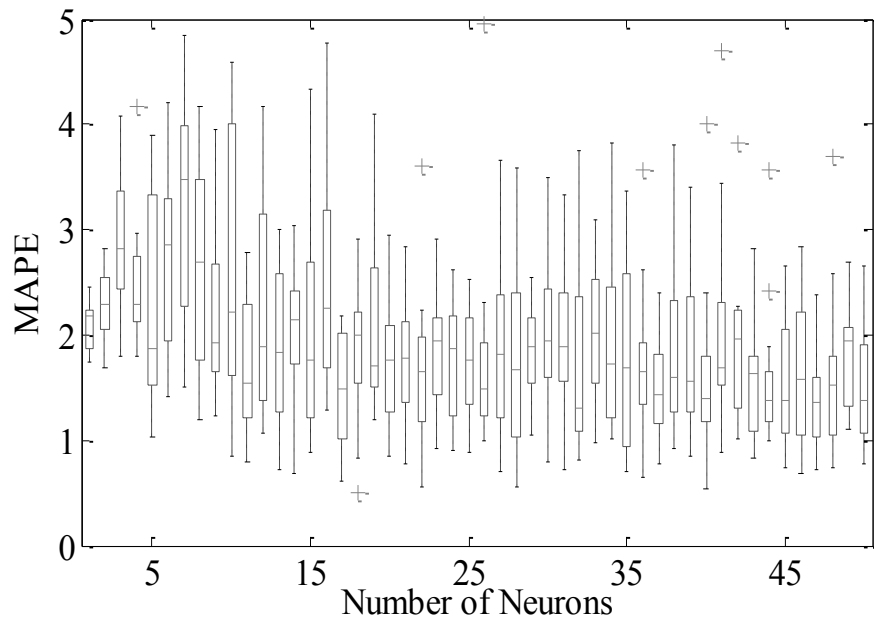


Figure 9. A zoom-in of 0-5% MAPE versus number of neurons in the hidden layer of the ANN.

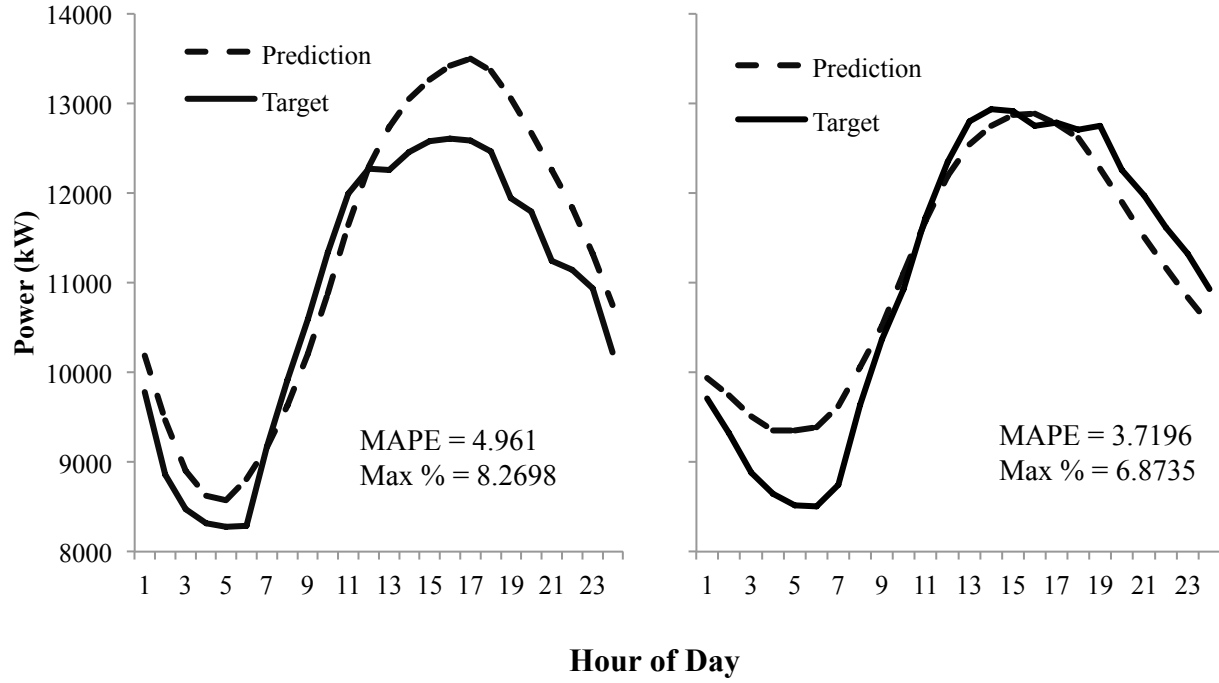


Figure 10. Examples of forecasts made with one neuron.

2.7.2 Forecast Errors

The average of the three predicted values corresponding to an hour of the day is considered as the forecasted value for that hour, as mentioned in section 2.6. The succession of all the hours (1-23) is considered the ‘forecast’ for that day, and the errors shown in Table 2 represent the average of all 242 ‘forecasts.’ It is noted that according to [38], errors in the range of 2-3% are considered normal for a prediction period of 24-hours. Since this corresponds to a utility scale, the errors corresponding to the ANN presented in this paper, as shown in Table 2, are acceptable. Figure 11 shows the distribution of errors by month.

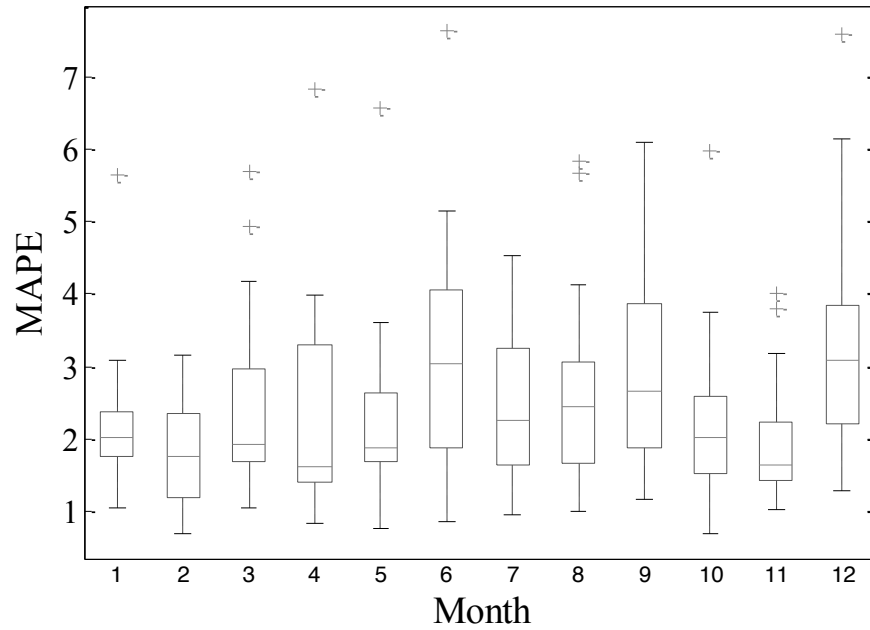


Figure 11. Distribution of MAPE by month.

Table 2. Average error associated with all 242 days forecasted.

MAPE	2.50
MPE	5.59
Energy Difference (%)	1.84

Figure 12 shows a histogram of the predicted peak hour of the ANN; on the x-axis is the difference (in hours) between the predicted peak and the actual peak. This is a measure of error that should be taken into consideration when evaluating the applicability of the forecasts. According to a Kolmogorov-Smirnov test, these data do not have a standard normal distribution at 5% significance. The following observations can be made from Figure 12: a) the ANN outputs with small time displacements between the predicted and actual values appear significantly more frequently than those outputs with larger time displacements between the predicted and actual values of the peak (i.e., greater than 3 hours, occurring at the tails in Figure 12). This may

present an issue when using the predicted outputs for DSM activities such as peak shaving, which require accurate predictions on the occurrence of the peak.

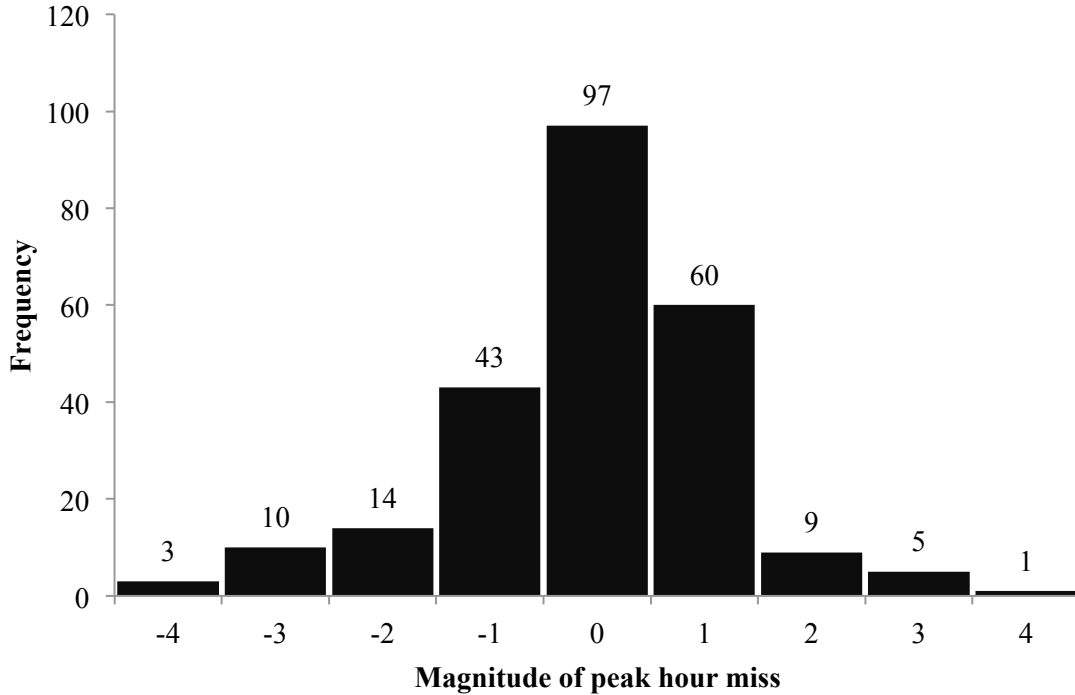


Figure 12. Error in peak hour prediction over 242 test days.

The difference in electrical energy consumption over a 24-hour period between the predicted and actual values is smaller than the MAPE not only because it looks at a different measure, but because the energy difference is averaged over negative and positive residuals. The MAPE is penalized for misses, both high and low, because it uses the absolute value of the residual. An example of a predicted load profile forecast is shown in Figure 13. The MAPE on the sample day is 0.90%, which is below the average value shown in Table 2. Figure 14 provides an indication on the performance of the ANN from the perspective of the MAPE. It is observed that the distribution is skewed to the left, although there are some days that provided relatively poor predictions. These poor predictions will be addressed in section 2.7.2.1.

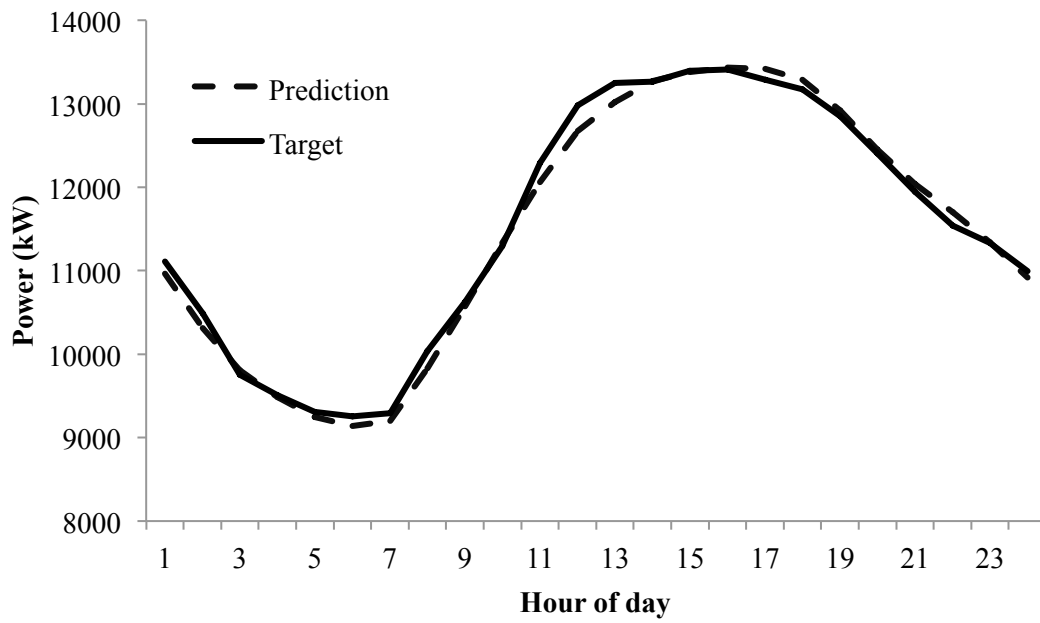


Figure 13. Typical load profile and forecast for 24-hour period.

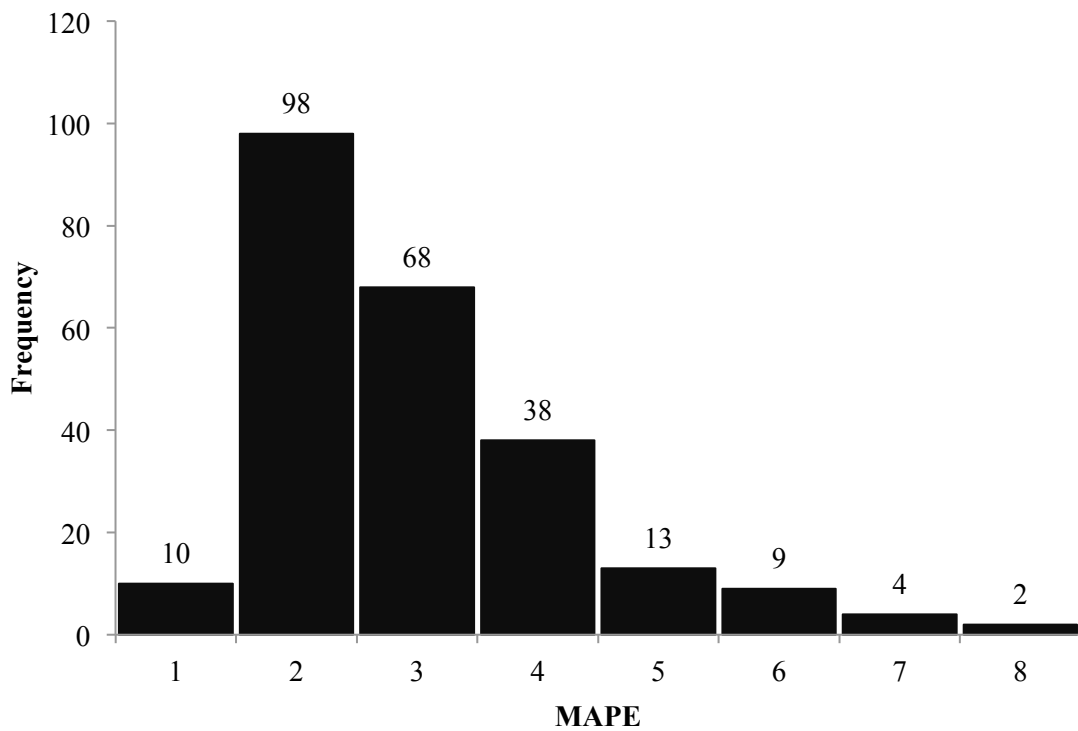


Figure 14. Distribution of MAPEs for all 242 test days.

2.7.2.1 Poor Forecast Results

Table 3 represents the forecasted days with MAPE above 4%. This is an attempt to understand why certain days do not yield forecasts with good accuracy. The right column provides a hypothesis of the high forecast error, as well as highlighted days that might have been affected by the explanation in the connected highlighted region. It can be ascertained from the hypotheses that the days where the occupation of campus is changed from previous days in series results in poor predictions. The days that have no hypothesis are not easily explainable by the academic calendar of CSU or are concomitant with perceptible weather variations, although it is conceivable that there is a simple explanation for all the days in Table 3. Approaches for recognizing these days are examined further in section 4.2.

Figure 15 presents a look at what time of day the worst forecast, or the MPE, happens. The trendline fitted to the data show that there is an increase in MPE occurrence as the forecast horizon increases. This is not surprising given that forecasted power later in the day is based largely off of the previous hours forecasts rather than real data. While this trend is likely to continue no matter what time of day forecasting is initiated, it is conceivable that changing the of initiation time to target ‘critical’ hours could improve the eventual implementation of this forecast tool.

Table 3. Days with MAPE over 4%.

Tuesday, January 18, 2011	First day back to classes
Tuesday, March 22, 2011	
Wednesday, March 30, 2011	
Thursday, March 31, 2011	
Monday, April 4, 2011	
Monday, May 16, 2011	Summer term begins
Friday, June 3, 2011	
Monday, June 6, 2011	
Wednesday, June 8, 2011	
Thursday, June 9, 2011	Big temperature drop
Wednesday, June 15, 2011	
Monday, June 27, 2011	
Wednesday, July 6, 2011	
Monday, July 18, 2011	
Monday, August 8, 2011	Classes ended Friday, Aug. 5th
Tuesday, August 9, 2011	
Tuesday, August 16, 2011	
Monday, August 22, 2011	Fall classes begin
Tuesday, September 6, 2011	Fifth was a holiday
Wednesday, September 7, 2011	
Thursday, September 8, 2011	
Monday, September 26, 2011	
Monday, October 3, 2011	
Monday, November 28, 2011	First day back from fall recess
Friday, December 16, 2011	Last Day final exams
Monday, December 19, 2011	Winter break
Tuesday, December 20, 2011	Winter break
Thursday, December 29, 2011	Winter break

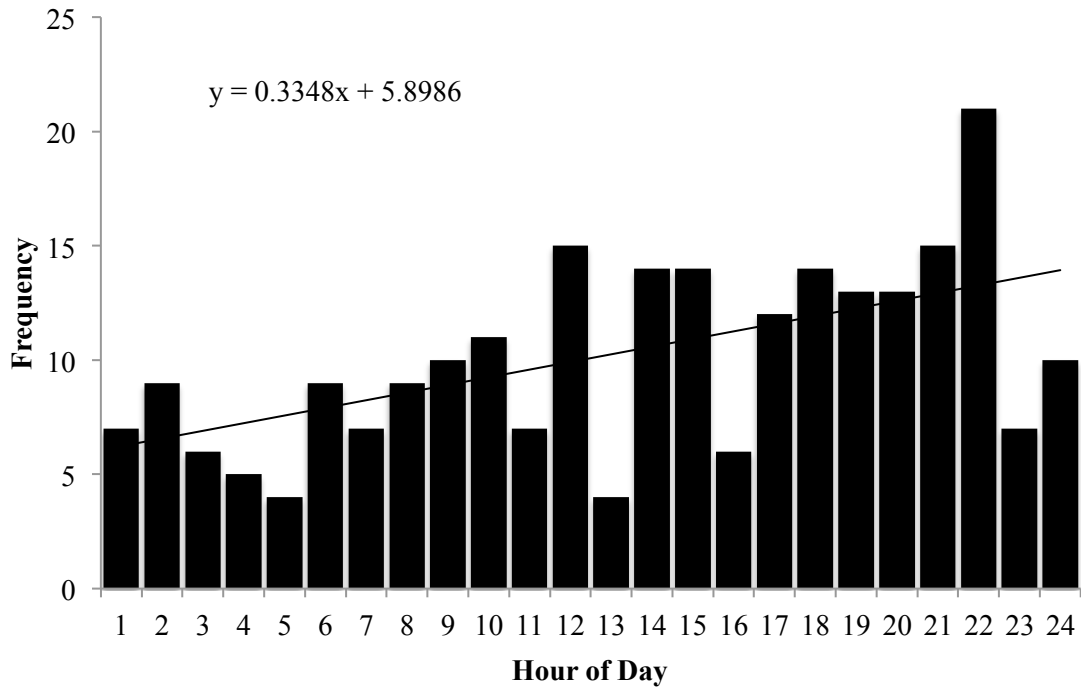


Figure 15. Frequency of maximum percent error based on hour of day. Equation represents the linear trend of the frequency.

2.8 Conclusions of Forecasting Algorithm

This chapter provided the techniques implemented, and the results, of designing an ANN for a university campus. Actual data from June 2006 to the test day in 2011 was used to present a realistic scenario using the ANN in real-time forecasts. The error in the daily electrical energy consumption suggests that this ANN could be useful in quantifying an energy savings goal. There are a number of applicable situations on a university campus that may provide an avenue for reconciliation between the comfort of the campus occupants and the opportunity for energy savings. This information could also be used in contract negotiations for energy saving measures with the local electric utility.

The previous section, 2.7.2.1, explores the poor results of the forecasting algorithm proposed in this chapter. It is useful to try and understand the characteristics of these days in order to

improve the forecasting as well as attach a level of confidence to each daily profile. It can be concluded from the analysis of that section that a relatively low level of confidence should be attached to days where there are drastic changes to campus occupancy from previous days, such as the first day of classes. Improvements to the forecasting are discussed further in section 4.2. The following chapter provides an EM scheme that utilizes the forecasts for projected energy and cost savings.

Chapter 3

ENERGY MANAGEMENT WITH A FORECASTED LOAD PROFILE

This chapter presents an EM philosophy based on controllable assets on CSUs main campus. As part of an effort by the Renewable and Distributed Systems Integration (RDSI) project, a DOE funded project being demonstrated in Fort Collins, CO, variable frequency drive (VFD) motors were installed in heating, ventilation, and air conditioning (HVAC) systems on two of the eight feeders on CSUs main campus. These were installed with the notion that power to these motors can be controlled when needed. The EM scenario presented in this thesis utilizes the potential power savings, which is 399 kW, of the VFDs for an estimate of cost and energy savings. The cost savings is based on the local utility, FCU, electric rate structure and electricity costs for 2012. The rate structure is not projected to change drastically in the near-term for customers in the GS-750 category such as CSU [5]. The EM is focused around the highest peak power on the regional power provider, PRPA, as this was determined to be the best opportunity for cost savings. The following section outlines the rate structure that the EM scenario is built around.

3.1 Fort Collins Utility Rate Structure

The customers of FCU are divided into rate structures by the phase requirements as well as the maximum power consumption of the facility being serviced. The categories are: residential energy, residential demand, general service, general service 25, general service 50, and GS-750, with subcategories based on other regulations/historical contracts, etc. [36]. There are a number of fixed charges based on metering points, infrastructure, as well as standby service and

transmission charges. The charges that are of concern for the purposes of this thesis are: energy demand, facility demand, and coincident demand, all of which will be covered in detail in the following sections, according to the 2012 rates [36]. These charges are variable based on the actions of the consumer, in this case CSU, and are consequently suitable for manipulation based on the objectives of the facility. The billing cycle for CSU is monthly, and therefore all components of the rate structure are calculated based on a monthly time step.

3.1.1 Energy Demand

CSUs main campus is subject to a different energy demand charge based on the season: summer or non-summer. The summer billing months are determined by the meter reading and can last no longer than three full billing cycles. These months are traditionally June, July, and August; and the charge for total energy during these months is \$0.0367/kWh. The non-summer rate, which is any month that is not determined to be in the summer billing period, is \$0.0349/kWh.

3.1.2 Facility Demand

The facility demand charge is designed to recover the costs of operating and maintaining the electric distribution system. It consists of a one-time per month charge during the highest integrated hourly power demand for the facility. This monthly charge cannot be less than 75% of the highest FP (in kW) occurring in the preceding eleven months. The charge for this hour is \$5.44/kW for the first 750 kW, and \$3.25/kW for every kW over 750 kW. This charge does not change according to season.

3.1.3 Coincident Demand

Coincident demand charge is a function of the monthly system peak for PRPA, the transmission and generation (T&G) utility responsible for generating and delivering to the municipal utilities: Fort Collins, Loveland, Estes Park, and Longmont, CO. The CP is the highest integrated hourly power demand for PRPA during a billing cycle. CSU is subject to the coincident demand charge over the integrated kW demand during that period. There are also two separate billing rates based on the same division of months for the energy demand. The rate for the summer months is \$10.20/kW, and for the winter months it is \$7.64/kW. The following subsection will expand on strategies that have been developed within FCU to mitigate the demand during CP. An example of the demand charges is shown in Figure 16. FP takes place at the highest power demand for the month, and CP on the highest power demand for the PRPA service area. The CP takes place in this month at the hour ending at 7 P.M. It is typical that the CP falls on a different hour than the daily or monthly peak for CSUs main campus.

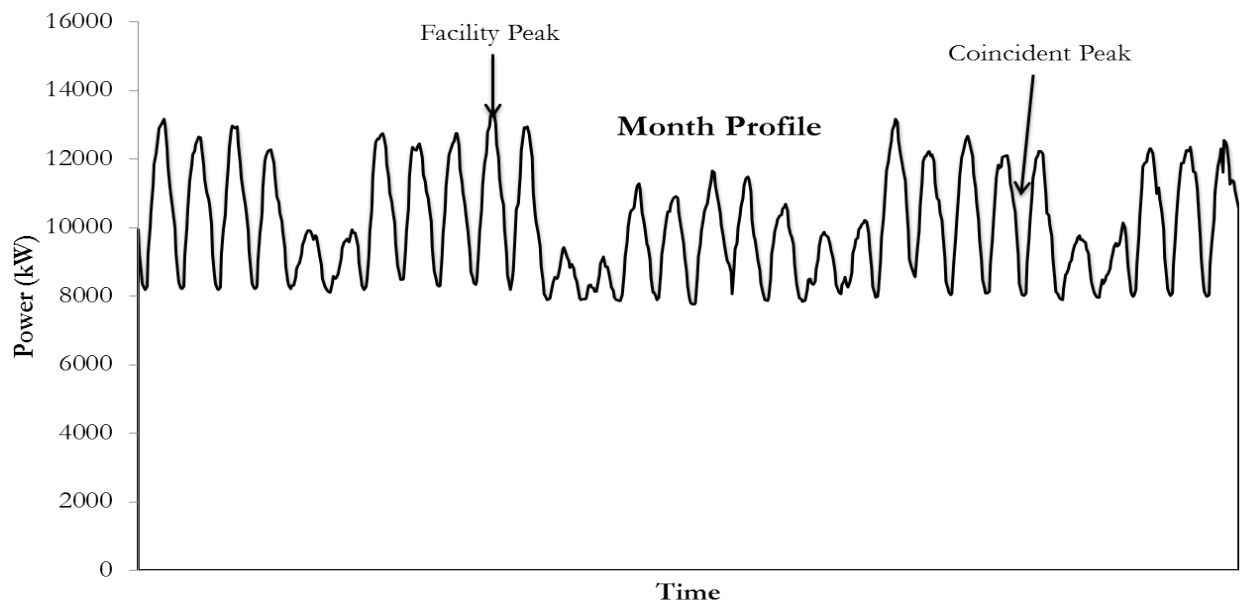


Figure 16. Example of FP and coincident peak occurrence in a typical monthly load profile. The energy demand charge is equal to the area under the load profile.

3.1.3.1 Coincident Peak Mitigation

According to FCU, CP is responsible for 23% of the bill for general service 50 and GS-750 customers [69]. This has led FCU to implement tools for these customers to utilize for management of their load during peak hours, which are referred to as control periods. A prediction of CP is necessary for these management tools, and is not an easy task given that this would require an accurate forecast for the whole billing cycle. Given the difficulty of predicting whether CP is going to happen on any given hour, the ‘hot shot’ signal was created in an effort to make the customers aware of a possible peak hour via email or other communication device. Hot shot is a subscription service from FCU that is available to the two largest customer categories, general service 50 and GS-750, as a service that gives warning to these customers as a informational tool for altering their load if they choose. According to FCU, the most cost-effective way to manage energy use is to reduce demand during CP [65].

The hours in which loads are managed based on hot shot signals are ‘control periods,’ of which 75 were employed in 2011. The time frame for the warning signal is anywhere from 30 minutes before the predicted peak, to within the predicted peak hour [5], [69]. The average duration for the control periods is two to three hours, and the response to these signals is a 50% reduction from subscribing customers during these control periods. This reduction can come in the form of shutting down operations in a manufacturing plant, or rescheduling non-essential loads [6].

3.2 Energy Management Philosophy

The EM philosophy adopted for this thesis is rooted in optimizing cost savings. This is not to say that the simulated actions were not motivated by recognition that saving energy, or from a

broader perspective, improving control and efficiency, was not also a goal. Optimistically, the cost reflects the improved efficiencies of the system as well as makes the reality of an EM strategy being adopted in the commercial market more viable. The following subsection will outline strategies that were considered and preliminarily tested in EM algorithms, as well as the final strategy utilized for the purpose of this thesis.

3.2.1 Target for Energy/Power Reduction

Three approaches to energy/power reduction were considered for the EM proposed in this thesis. These are heavily contingent on the rate structure that CSU is subject to, which was outlined in section 3.1. These strategies include: reducing overall energy usage, reduce the FP, and reduce the demand during the CP. There are separate challenges as well as advantages associated with each approach, which will be discussed in the following subsections.

3.2.1.1 Energy Demand Reduction

The concept of energy demand reduction is problematic in that it requires one of three things: more efficient operating equipment, a change in comfort levels for campus occupants, or a change in behavior for campus occupants. Installation or simulation of new equipment is outside the scope of this thesis, although it is plausible that updated equipment could be justified based on conclusions of this thesis, which will be articulated in greater detail in section 4.2. It is conceivable that simulated actions of this thesis would affect the comfort of occupants, although quantifying the impact was outside the scope of this thesis. An example of energy demand reduction is provided in Figure 17 and Table 4. The reduction scenario reduces the energy demand every hour, which results in the load profiles of Figure 17. The predicted load profile is the prediction that is made by the algorithm presented in chapter 2. The ‘Predicted minus 1% of

predicted' curve is representative of what the adjusted load profile would look like to an operator when pre-emptively deciding on actions to meet the goal of 1% energy reduction.

Table 4 exemplifies the actions that must be taken based on the forecasts to achieve a 1% energy reduction during every hour of the day. The use of a predicted load profile allows for actions to be taken pre-emptively to achieve the 1% reduction. It can be ascertained from the Table that these actions would result in an energy reduction that is very near the goal of 1%, even though they are based on actions that could be decided hours in advance from the forecasted profile. The associated cost savings from the energy demand charge for this example day is \$92 for a total energy savings of 2636 kWh.

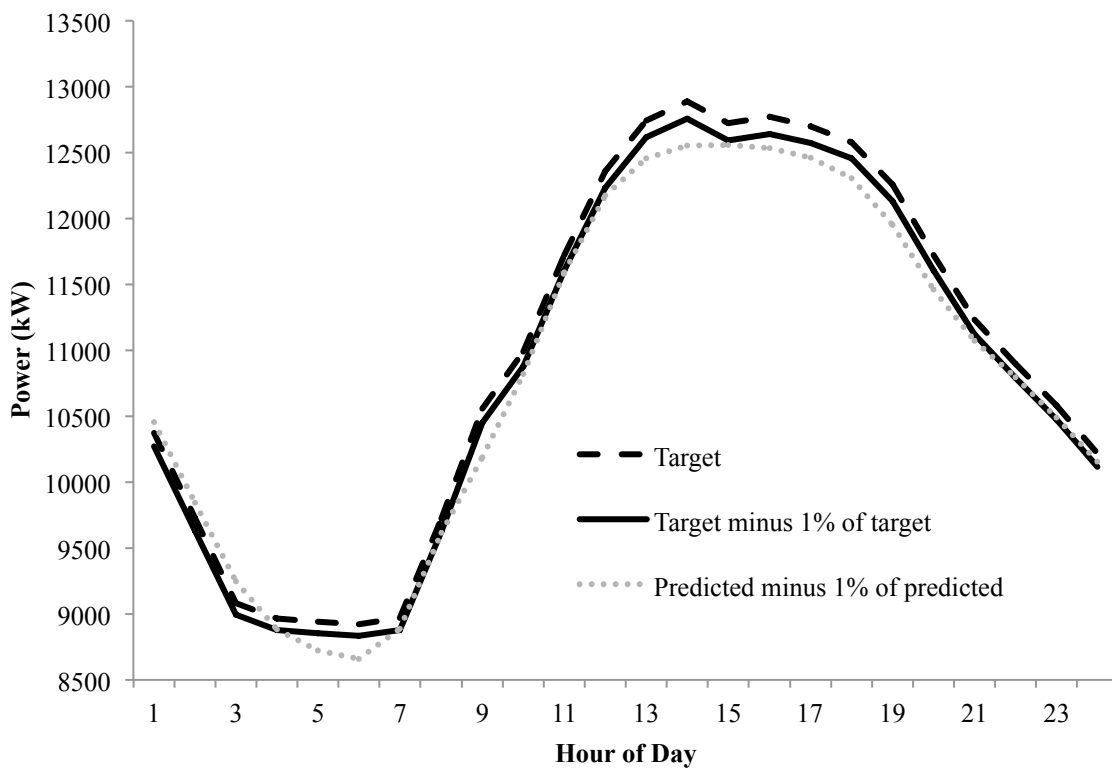


Figure 17. Energy demand reduction of 1% on a typical load profile for CSU.

This strategy faces the challenges of regulations for indoor air quality and ventilation [70], [71], and was determined to be less lucrative and less realistic than the final EM strategy implemented in this thesis. An advantage of this strategy is that the controllable assets needed for each hour load shedding are less than the FortZED assets of the proposed reductions of section 3.2.1.3. This point can be ascertained from Table 4, which anticipates shedding to not exceed 130 kW.

Table 4. Data from typical electrical load profile of CSU, and simulated 1% energy demand reduction.

Hour of day	Predicted 1% reduced demand profile (kW)	Actual 1% energy demand reduction (kW)	Difference in energy demand reduction (kW)
1	105.6	104	1.9
2	99.4	97	2.2
3	93.4	91	2.6
4	89.7	90	0.1
5	88.1	89	-1.3
6	87.4	89	-1.8
7	89.8	90	0.1
8	97.2	97	-0.1
9	102.9	106	-2.6
10	109.3	110	-0.6
11	117.1	117	-0.2
12	123.0	124	-0.6
13	125.9	127	-1.6
14	126.8	129	-2.1
15	126.9	127	-0.4
16	126.6	128	-1.1
17	125.9	127	-1.1
18	124.3	126	-1.5
19	120.7	123	-1.9
20	115.8	117	-1.5
21	111.9	112	-0.5
22	109.0	109	0.0
23	106.0	106	0.1
24	102.6	102	0.4

3.2.1.2 Facility Peak Demand Reduction

Reducing the peak power of the facility requires knowledge of when the peak power for the day will occur, as well as knowledge of the peak for the month. Figure 12 shows the ability of the ANN described in chapter 2 to predict when this will happen on a daily basis, but the forecasting algorithm discussed in chapter 2 does not cover the foresight necessary to predict the peak for the month. It is conceivable to reduce the peak every day based on the predictions and on the controllable assets, although the marginal cost of electricity during FP (\$3.25/kW) is less than half the marginal cost of electricity during the CP in winter months (\$7.64/kW) with an even greater difference in the summer months (\$10.20/kW). This discrepancy indicates that controlling assets during CP is more lucrative than during FP.

3.2.1.3 Coincident Peak Demand Reduction

CP reduction is a concept that was outlined briefly in section 3.1.3.1, although the strategy applied in this thesis is fundamentally different in at least one significant way. The actions taken during a hot shot signal are reactionary, and are subject to the signals sent from FCU. The actions taken by CSU in response to these signals is unclear, although there is some form of load shedding according to the facilities management office [72], [73]. The CP reductions for the purposes of this thesis are simulated for every test day, and are based on the historical CP's for PRPA (Figure 18). The occurrence of CP days from June 2006 to December 2011 is represented by the numbers in the boxes, which are placed in the month and time slots for which the CP occurred. Details of the simulation are provided in section 3.4.

3.3 *Manageable Assets*

The assets that are controlled in the EM simulation are the speed setpoints of the VFDs, as explained in the chapter introduction, and represent a maximum of 399 kW on two feeders on CSUs main campus. Figure 19 represents a fabricated feeder configuration of CSU. The actual feeder configuration is withheld for security purposes. Feeders one and four represent the VFD loads that are controllable by facilities management, equaling 399 kW from 49 fans (The details of the VFD assets are in appendix B). The means and schedule that CSU facilities management uses to control these loads is unknown, although it is clear that they are capable of being controlled at certain times [73]. Feeders one and four are considered to be controllable at the feeder level, i.e. 100 kW, no less and no more, can be shed from feeder four at any given time.. The same scenario is true of feeder one; 299 kW can be shed at any given time. The following section outlines how these assets were treated in the EM scenario utilized for this thesis.

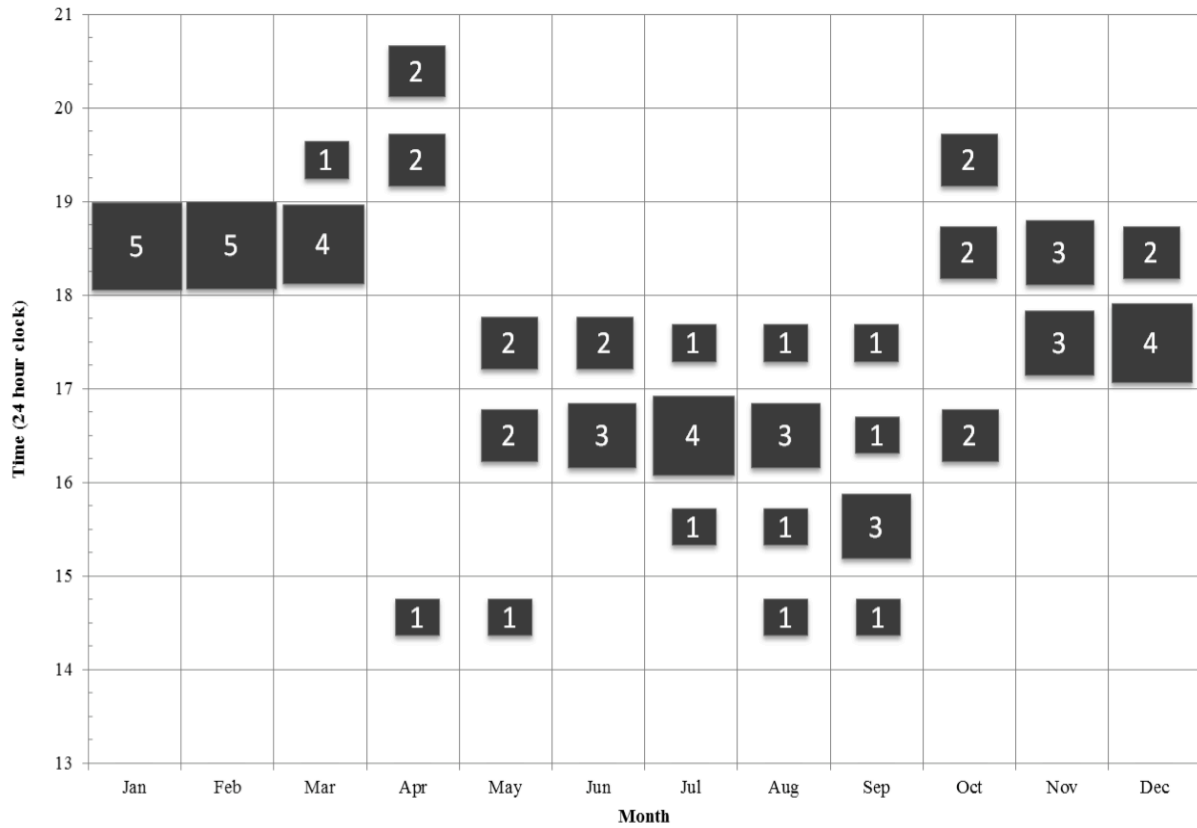


Figure 18. Coincident peak hour occurrences from June 2006 through December 2011 [5] (This Figure was partially created by Adam Zipperer, CSU, and Pablo Bauleo, FCU).

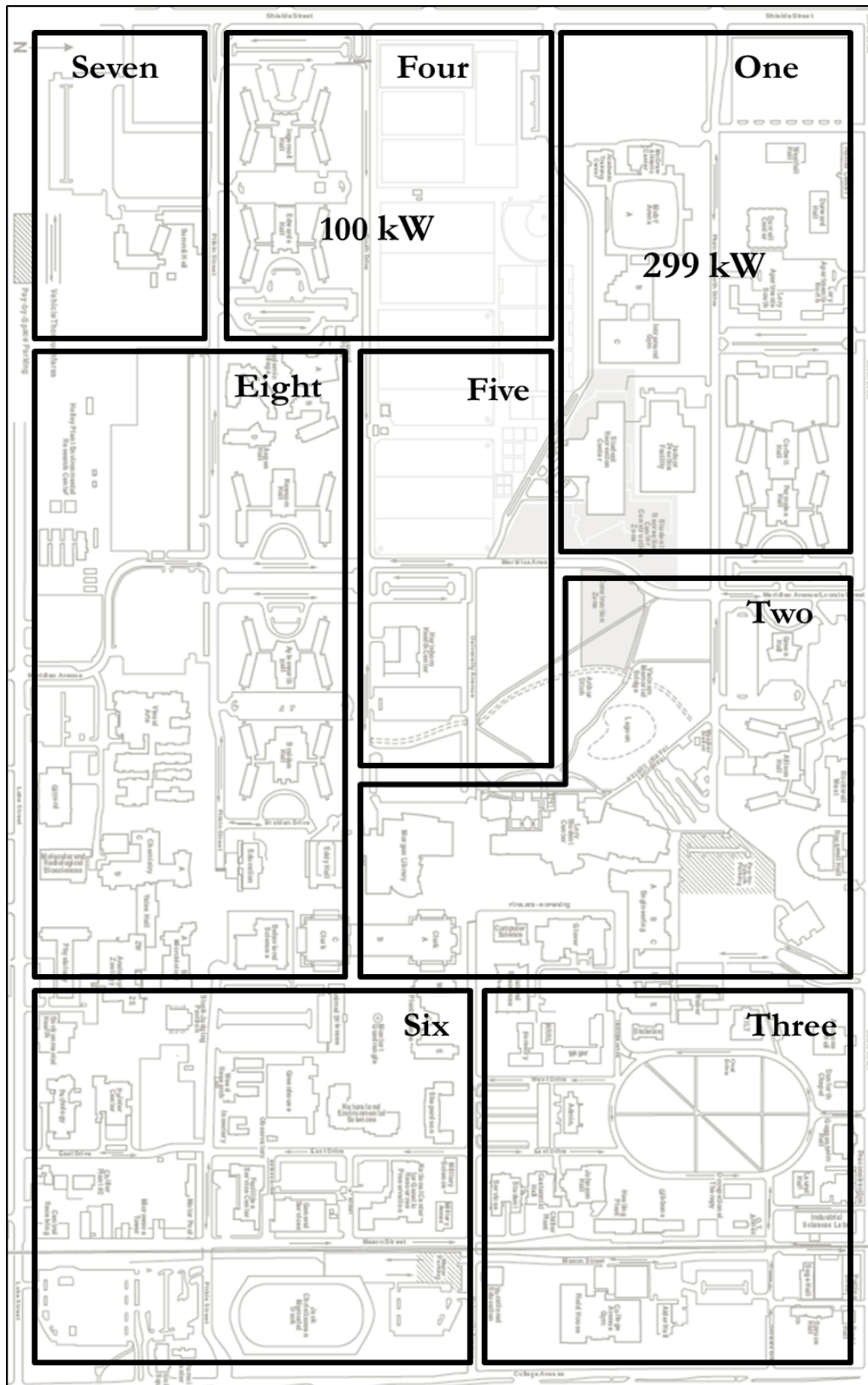


Figure 19. Fictional feeder configuration for CSU's main campus [74]. Feeders one and four have the assigned amount of controllable load in the form of VFD's.

3.4 Energy Management Simulation

The management of loads is divided into two scenarios: ‘one-hour’ capability, and ‘two-hour’ capability. Each scenario refers to the allowed scheduling and cycling of the VFDs according to the CP probability of occurring. These probabilities are based on the historical data from Figure 18. The primary goal in looking at the probabilities of CP is to shed the maximum amount of load over the most probable hour of CP. Figures 20 and 21 shows the one-hour and the two-hour schedules that are implemented in a cost savings analysis that will be presented in the next section. The numbers in the boxes refer to the feeder that is being shed, and B means both feeders are shedding loads. As an example, in March, for the one-hour scenario, 299 kW are shut-off in the hour ending at 19, and 100 kW are shed in the hour ending at 20.

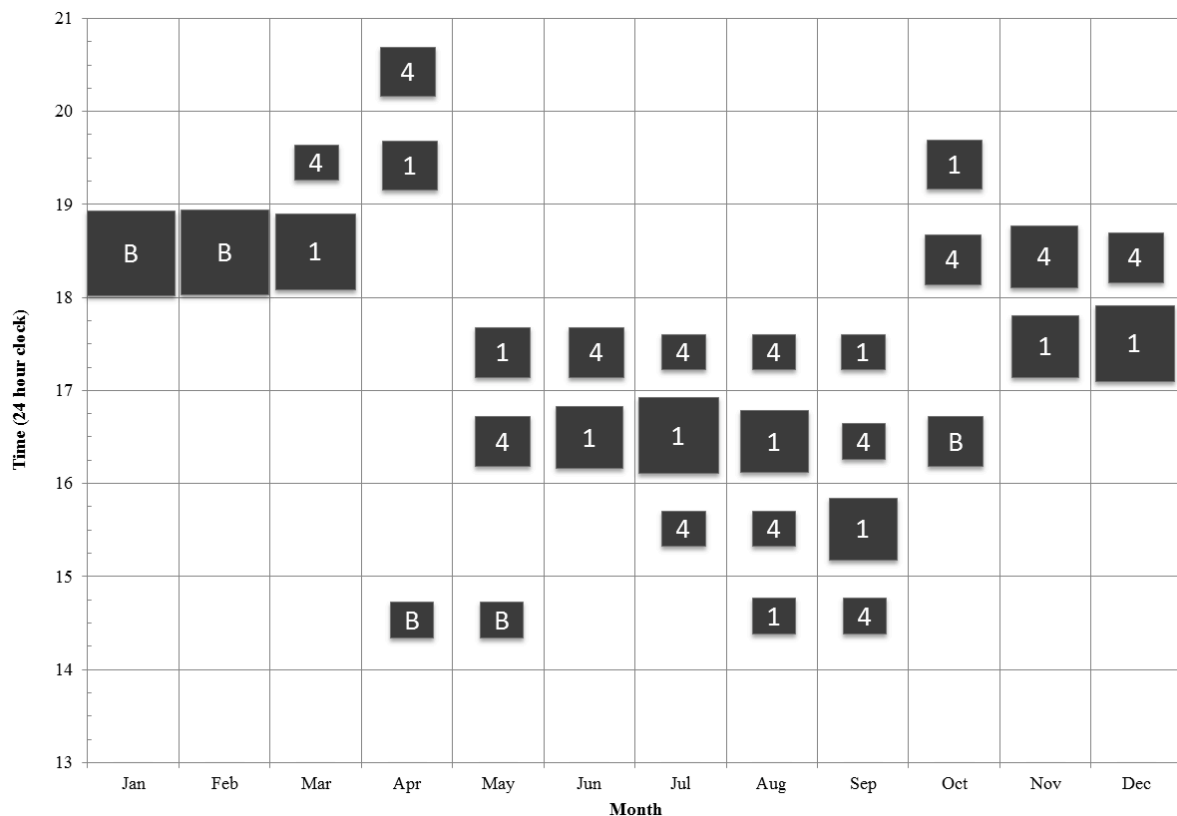


Figure 20. The one-hour scenario of managing loads based on the CP probability.

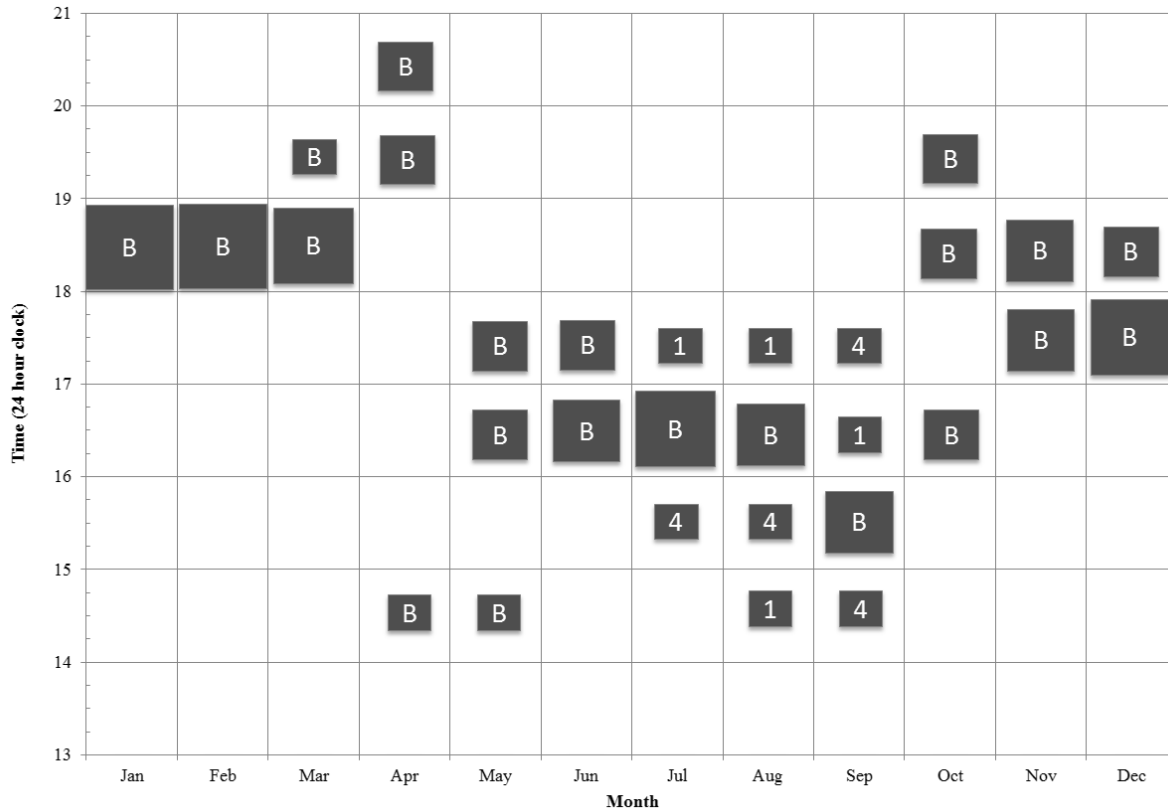


Figure 21. The two-hour scenario of managing loads based on the CP probability.

The one-hour schedule allows for each individual feeder to shed load for no more than one hour, with a one-hour recovery time until those assets can be utilized for shedding again. The two-hour schedule allows for each feeder to shed load for two-hours consecutively, with a one-hour recovery time just as in the one-hour scenario. These schemes are meant to reflect, from a crude estimate, the thermal lag that is common in many commercially sized buildings. If HVAC assets are shed, a change in air temperature is not going to be felt for some setpoints of the air handlers. It is assumed that this is roughly one hour for the purposes of this thesis, and that a building or group of buildings can recover to a steady-state after one hour of normal operation. The energy needed to recover to the building or feeder setpoints is not taken into account in these

models. An example of a one-hour load-shedding scenario is shown in Figure 22 and a two-hour scenario is shown in Figure 23.

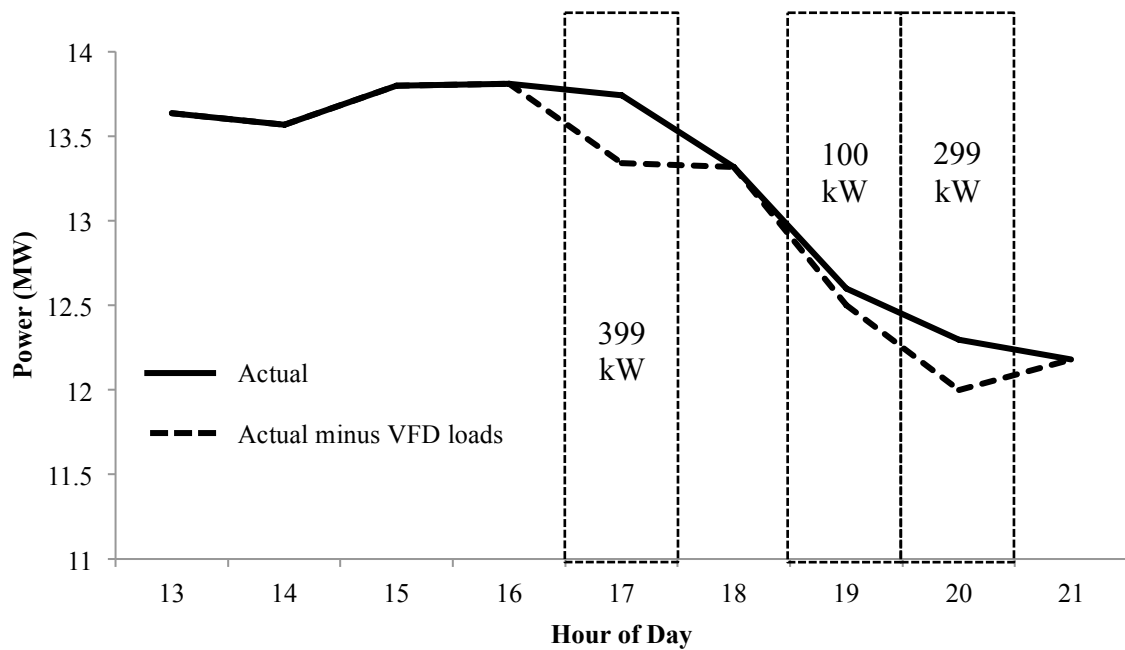


Figure 22. Load profile for a day in October with the load managed profile of a one-hour scenario. Dashed boxes represent load shed hours.

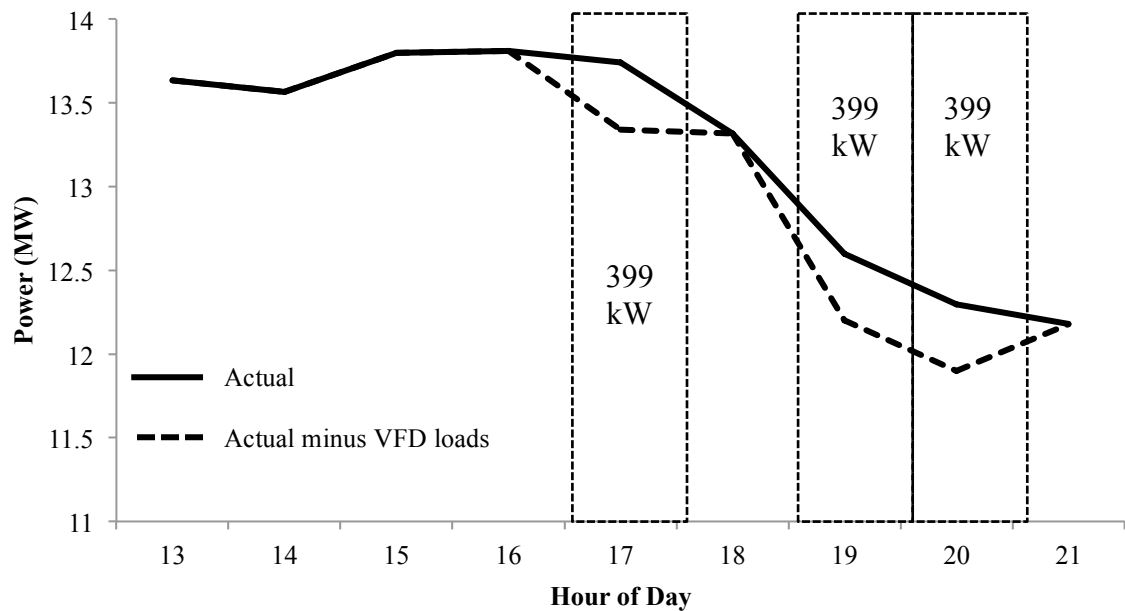


Figure 23. Load profile for a day in October with the load managed profile of the two-hour scenario. Dashed boxes represent load shed hours.

Figures 22 and 23 shows the load shedding for a day in October. The one-hour scenario results in the load-shedding as follows: for the hour ending in 17, 399 kW are shed, for the hour ending in 19, 100 kW are shed, and the hour ending in 20, 299 kW are shed. The two-hour scenario allows for all 399 kW to be shed all three hours of probable CP. Figures 20 and 21 show the load shedding scheme for all months.

Calculation of cost savings and projected cost savings uses the electric rates outlined in the sub-sections of 3.1, multiplied by the kW or kWh saved during each day. The values provided in the next section are daily averages or sums over the whole billing cycle. These values include only the actual savings that resulted from the actions outlined previously in this section, which does not apply the use of the forecasts that can be provided by the ANN. The utilization of the forecast is addressed in section 3.6. The implications of the forecasts effecting the final actions of the operators will be discussed briefly in section 4.2.

3.5 *Results of EM*

The results of the EM scenario outlined in the previous sections are presented here as cost savings and the average daily energy savings over the billing cycles of 2011. As mentioned in section 3.1, the savings are based on the 2012 rates for FCU. Again, the energy required recovering to the building setpoints are not modeled in these scenarios.

The discrepancy between one and two-hour scenarios is largely based on the ability to shed all available 399 kW during more probable CP hours, therefore increasing the chance that CP will land on the maximum load shed. There is also a greater energy cost savings in the two-hour scenario because of the additional load taken off the schedule, which can be acknowledged by the greater saturation of 'B', or 399 kW shedding periods, in Figure 21 than in Figure 20. The leading cost savings during CP, evident in Figures 24 and 25, was the goal of the heuristic EM.

Table 4. Summary of energy and cost savings for one-hour scenario.

	Avg. Energy Savings (kWh)	Energy Cost Savings (\$)	Facility Peak savings (\$)	Coincident Peak Savings (\$)	Total Cost Savings(\$)
January	0.11	278.50	0.00	3048.36	3326.86
February	0.15	431.68	0.00	3048.36	3480.04
March	0.16	431.68	0.00	2284.36	2716.04
April	0.26	724.11	0.00	2284.36	3008.47
May	0.31	849.43	0.00	3048.36	3897.79
June	0.19	559.60	0.00	1020.00	1579.60
July	0.16	540.55	971.75	1020.00	2532.30
August	0.23	820.10	325.00	1020.00	2165.10
September	0.27	877.72	1296.75	764.00	2938.47
October	0.29	863.36	971.75	3812.36	5647.47
November	0.21	612.70	0.00	764.00	1376.70
December	0.18	501.30	0.00	2284.36	2785.66
Annual	0.21	7490.72	3565.25	24398.52	35454.49

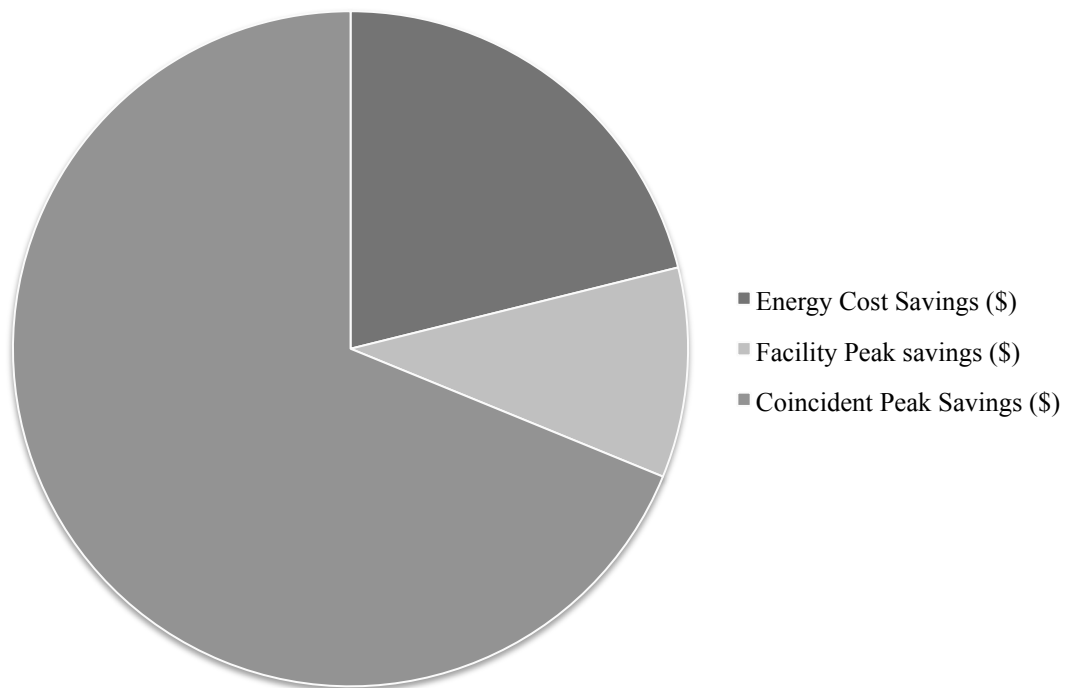


Figure 24. Proportion of cost savings attributable to each demand related charge from FCU.

Table 5. Summary of energy and cost savings for two-hour scenario.

	Average Energy Savings (kWh)	Energy Cost Savings (\$)	Facility Peak savings (\$)	Coincident Peak Savings (\$)	Total Cost Savings(\$)
January	0.11	278.50	0.00	3048.36	3326.86
February	0.15	431.68	0.00	3048.36	3480.04
March	0.25	682.33	0.00	3048.36	3730.69
April	0.40	1127.93	0.00	3048.36	4176.29
May	0.47	1281.11	0.00	3048.36	4329.47
June	0.34	1007.79	0.00	4069.80	5077.59
July	0.28	920.37	1296.75	3049.80	5266.92
August	0.33	1160.27	325.00	1020.00	2505.27
September	0.32	1060.74	1621.75	2284.36	4966.85
October	0.40	1190.68	1296.75	5332.72	7820.15
November	0.35	1023.51	0.00	3048.36	4071.87
December	0.34	922.55	0.00	3048.36	3970.91
Annual	0.31	11087.48	4540.25	37095.20	52722.93

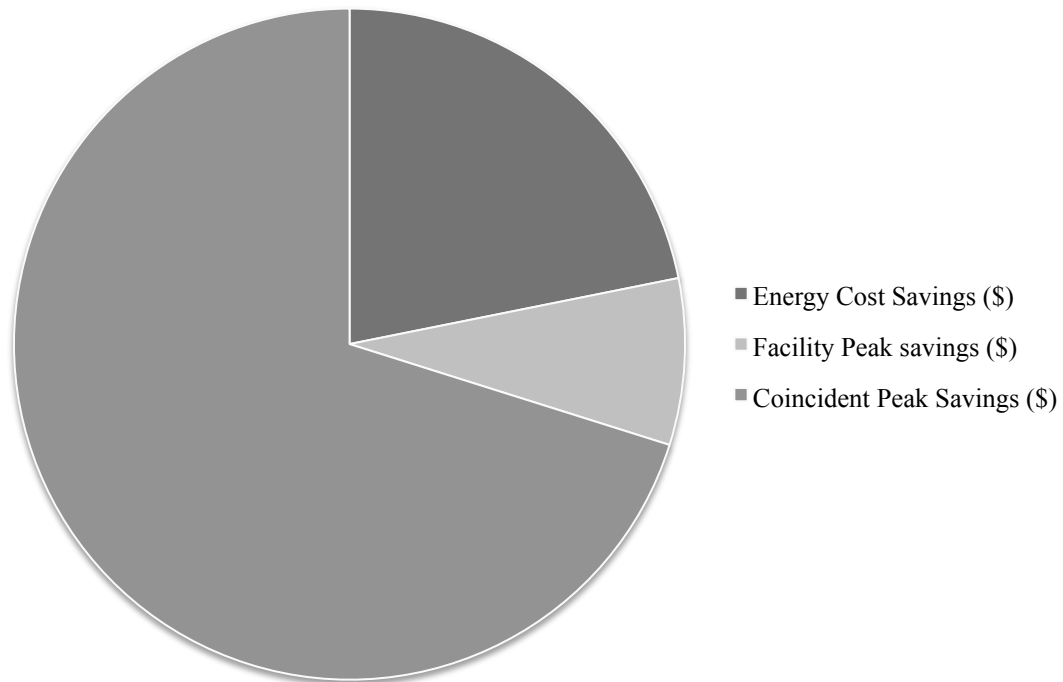


Figure 25. Proportion of cost savings attributable to each demand related charge from FCU.

3.6 Energy Management Utilizing Load Prediction

The EM laid out in the previous sections of this chapter provides a pattern of actions that will likely result in the savings similar to those shown in Tables 4 and 5. A more realistic approach to how this EM will be implemented is provided in this section, with utilization of the forecasted load profiles as a tool in load management decisions. While it is hard to determine the eventual value of the predicted load profile to decision makers, an attempt will be made to assume the ultimate objectives of operations with a biased toward energy savings and cost savings on similar parallels with occupant comfort.

3.6.1 Using Forecasts for Energy Management

Data about the following day gives decision makers an accurate depiction of the electrical load for the day, but also allows for better assumptions about the impact that load management might have on the comfort of the occupants. Figure 26 and Table 6 provide an example of what could be provided to the decision makers, such as the facilities management of CSU. Figure 26 shows two load profiles: the forecast for the day, and the forecast with the EM of section 3.5 implemented. The value of an operator seeing the load profile is hard to quantify, although it undoubtedly gives an indication of where the demand of the campus will be when load shedding occurs. Given the accuracy of the forecasts from section 2.7.2, it can be assumed that the profile is a good indication of what will happen, and can therefore be accepted as such.

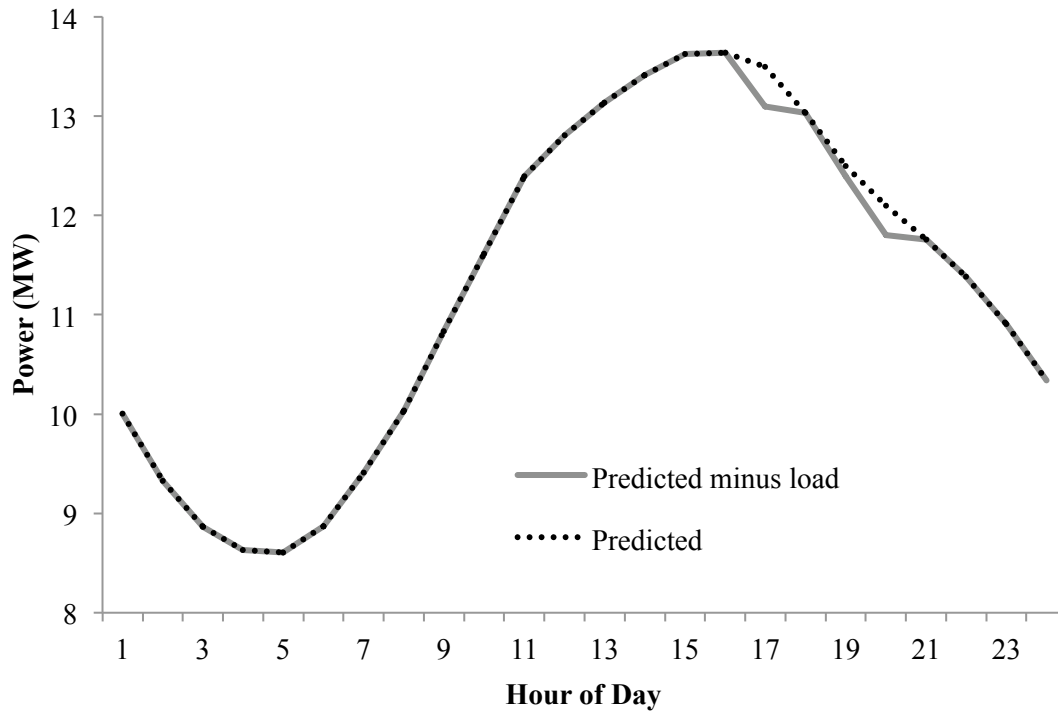


Figure 26. Forecasted load with a projection of EM.

Table 6 provides the cost and energy savings that will result from the load shedding scheme laid out in the previous section, and the load profile of Figure 26, as well as projections for possible FP and CP scenarios. The CP cost savings is an amount that includes the energy demand savings, since this will be included in the total when CP occurs.

Table 6. Example of table that could be provided to operators and decision-makers with daily load predictions.

Energy Demand (kWh)	798
Energy Demand (\$)	28
Coincident Peak – hour 17 (\$)	3076
Coincident Peak – hour 19 (\$)	791
Coincident Peak – hour 20 (\$)	2312

3.7 *Concluding Notes on Energy Management*

The EM proposed in this chapter provides a clear means for cost savings with no additional hardware or installations to the main campus of CSU. This is assuming that CSU will be moving toward real-time power data availability, which is a good assumption given that many buildings have recently been furnished with power quality meters capable of connecting to the local area network for real-time access. The savings potential shown in Tables 4 and 5 are a good indication of what can be achieved following the EM algorithm proposed with the current rate structures for CSU. It is conceivable that the actions proposed would be affecting occupants of the campus a great deal, although the potential savings in energy and cost justifies further investigation.

It is also worth noting that the potential savings could be greater in an area where ToU rate structures are being implemented more aggressively, such as PG&E, which has higher rates during higher probability peak hours [11]. FCU has a relatively low amount of demand related charges and is therefore a tougher area for demand savings. While the scenarios presented in this chapter are specifically developed for FCU rates, it is plausible that the philosophy behind this could be modified for use in another utility.

Chapter 4

CONCLUSIONS AND FUTURE WORK

4.1 *Conclusions*

The algorithms presented in this thesis provide a toolset that permits a better understanding of the electrical energy consumption of the end-user, as well as provides an actionable means for active participation in consumption, as opposed to the more widely accepted passive participation. The implications of this sort of participation cannot only be beneficial to the end-user, as is shown in chapter 3, but can also provide relief to the stressed electrical grid given adoption of similar algorithms by numerous end-users.

Chapter 2 presented an example of applying algorithms that have been utilized by the utility industry for use on a commercial scale. The success of this application makes it plausible that other algorithms developed at a utility scale can be transferred and used at the commercial, or possibly smaller, scale. Several of the performance measures evaluated in this thesis are, to the best of the author's knowledge, unique, and offer a good indication of how this particular algorithm can be optimally utilized.

The following can be concluded from the error measures of Table 2, and Figures 12 and 14:

- | | |
|------|---|
| i. | The ANN is a better predictor of energy-use over 24-hours than power. |
| ii. | The majority of forecasts predict within one hour of the peak. |
| iii. | The majority of forecasts provide an 'acceptable' MAPE [38]. |

The employment of this forecasting algorithm should take into account the conclusions outlined in this list. For example, in the analysis of the 'peak hour miss,' a level of confidence could be ascertained based on the results of the forecasts. Figure 12 provides the information necessary to attribute a level of confidence that an operator could take into account. Looking at a prediction

for the day, the operator should be 40% confident that the peak hour has been predicted correctly based on the probability of 97 correct peak predictions per 242 days. Similarly, actions taken based on hours late in the day should take into consideration that MPE is highest in the hours farthest from the prediction time.

The EM presented in chapter 3 presents an analytical, pre-emptive, rather than the traditional reactionary, solution to the problem of EM. The use of historical CP data is demonstrated in section 3.5 to be an effective way to maximize the value of the installed VFDs. Employing historical evidence in the EM algorithm allows for a well-established plan of action given a set of goals, which in this case is maximum cost savings. The value of the foresight permitted by this EM algorithm is two-fold: 1) the responses to the actions of the operator can be better determined when taken in the context of the predicted load profile, and 2) the value of those actions can be evaluated more accurately than with a subjective cost-benefit analysis. While the actions simulated in chapter 3 might not always be employed for load shedding, it is assumed that the decision-making would be sound, and that the cost savings is reflective of a plausible scenario. The savings laid out in chapter 3 is therefore considered to be significant given that no additional hardware installations are needed. The assumption of no hardware installations is reasonable given that CSU is moving toward real-time power data availability in many of their buildings, and it is likely that data-logging hardware is inevitable.

4.2 Discussion

The ANN forecasting algorithm presented in chapter 2 has multiple avenues that should be explored to improve predictions. The most lucrative of these avenues is likely in the pre-processing of the data. While weekends and holidays were excluded, the judicious approach for this exclusion could be more robust and potentially include mathematical or statistical

approaches, or could be based upon additional sensor measurements which assess activity levels or occupancy. Preliminary exploration included the utilization of clustering algorithms to separate days that do not have similar load profiles, although these were discarded in favor of subjective parsing. It is recognized that further exploration of these or other ‘outlier detection’ techniques could be useful in automating the pre-processing of the data.

Additionally, the notion of sensing the activity level of campus or certain buildings was explored as a means for adding to the input variables for prediction, or for indications about which ‘type’ of day the campus is currently operating. This sensing application is being explored further at the EECL at CSU.

Other improvements to the forecasting could include a greater focus on certain aspects of the forecasts, such as reducing the FP or the CP error. This could be explored within the context of the proposed algorithm, or as an additional forecasting algorithm that would work in conjunction with the proposed.

The implementation of this forecasting algorithm in a real application would utilize forecasted weather data, which was unavailable for the modeling described in chapter 2. The use of weather forecasts for the inputs to the network would give a better representation of how the forecasts would act in real-world applications. It could also indicate areas for improvements or network architecture modifications that would improve performance.

Further research into the EM proposed in chapter 3 should analyze the impact of the proposed load shedding. The proposed algorithm presents operators with the decision to take action based on their opinion of how the thermal comfort of the occupants will be affected. While this is considered to be sufficient for a nascent algorithm of savings, a more robust option to operators would give indications of the effects of their actions. Indeed, similar ANN

techniques, potentially coupled with physical building models, could be utilized to estimate the impact of energy management actions on building functions, such as occupant comfort.

Another improvement to the proposed EM would eliminate load shedding days based on an additional forecast of CP on the whole of PRPA's service area. FCU sent 75 hot shot signals in 2011 [69], which indicates the challenge associated with predicting CP. The existence of a forecast for PRPA could greatly reduce the amount of days that CSU would have to decrease the comfort of its occupants.

The effect of having a predicted load profile for the following day is not wholly predictable. It is plausible that the information will have greater impact on the proposed operators of commercial control systems than is assumed in this thesis. An example of this would be the scenario proposed in section 3.6. The familiarity with such a scenario would likely result in increased acumen of the operator to the impact that actions will have on the occupants, whether based on the shape of the predicted load profile for that day, or based on the expected activity on campus that day.

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APPENDIX A

Matlab® Script for calling ANN function:

```
% %% CSU-ANN operating instructions

% Available on T:\projects\CSUBEM\CSU_ANN
%
% One day forecasts are produced for any day in the dataset via
'FORECAST_2011.'
% -Dates can be changed for the day you wish to forecast
% -The bottom section of 'FORECAST_2011' has the ability to run the
function
% but 'NARX_fulltime,' which runs forecasts on all days including
weekends and holidays.
% Needs work to get it working correctly.
%
% -'NARX_occupied.m' is the ANN algorithm
% -refer to this for comments about changing the parameters of the
ANN

% - Important outputs from Forecast:

% -ypred is the vector of forecasted power
% -pred_target is the vector of target variables
% -net is the structure that contains the information about the
ANN, i.e. weight matrices, design, etc.

% - Each forecast trains data for dates July 1, 2006 to whatever date is
specified in
% 'FORECAST_2011.'
%
% The whole 2011 year is forecast using 'FORECAST_2011.' This will step
through all 'occupied days'
% in 2011 and produce a workspace that should be saved and run through
Pred_structureplace after 3 separate, saved, workspaces.
%
% Taken from U:\MATLAB\Campusdata\ANN\CSU_ANN\Add_data\AA_Read_first.m
% ANN
% FORECAST_2011.m. Run it three times and save each
% workspace as a unique name
%
% Post-ANN
% 'Predict_structureplace.m' is to be run after
% 'FORECAST_2011.m' is run 3 times. The file names in each
% loop in Predict_structureplace.m have to be changed to match
the new
% filenames created after one run of
Step_through_Predict_splitdata.m
% This is not completely automated because the overnight runs
would often
% have erroneous forecasts depending on some reboots or other
computer
% glitches that caused training to stop early. It was easiest
just to look
```

```

%           %   at each forecast before doing another one.
%
%   Structures:
%
%   CSUPower.mat: named 'C' in the workspace
%
%   FULLKW: [48240x1 double]           All power values from the dates
specified in C (July 1, 2006, 1:00-Jan 1,2012).
%   FY07: [1x1 struct]               Power broken out by fiscal year
%   FY07FY11: [43824x1 double]       Power from fiscal year 2007-
2011
%   FY08: [1x1 struct]
%   FY09: [1x1 struct]
%   FY10: [1x1 struct]
%   FY11: [1x1 struct]
%   FY12: [1x1 struct]
%   fulltime: [48240x1 double]       Dates for all available power
values
%   holidays: [48240x1 double]       vector of 'true' 'false'
holidays
%   hour_fulltime: [48240x1 double]   vector of the hour of the day
in matlab time
%   weekday: [48240x1 double]         Vector of weekday (1-7)
%   weekdays: [1x1 struct]           Structure with date, hour, and
KW of weekdays
%   weekend: [1x1 struct]             Structure with " " "
%   coinpeakvector: [1x66 double]    Date vector for coincident
peaks over time period
%
%
%   POWER_split.mat: named 'S' in workspace (called in ANN algorithm
NARX_occupied.m)
%
%   This structure is created in 'Weeksplit.m' (refer to
U:\MATLAB\Campusdata\ANN\CSU_ANN\Add_data\AA_Read_first.m)
%   -split CSUPower into weekends and weekdays
%
%   weekend: [1x1 struct]
%   weekday: [1x1 struct]
%
%   S.weekday
%   Power: [18177x1 double]
%   date: [18177x1 double]
%   hour: [18177x1 double]
%
%   WEATHER_split.mat: named 'T' in workspace (called in ANN algorithm
NARX_occupied.m)
%
%   This structure is created in 'Weeksplit.m' (refer to
U:\MATLAB\Campusdata\ANN\CSU_ANN\Add_data\AA_Read_first.m)
%   -split CSUPower into weekends and weekdays
%
%   weekend: [1x1 struct]
%   weekday: [1x1 struct]
%
%   T.weekday
%   temp: [30063x1 double]

```

```

%          sun: [30063x1 double]
%          relhum: [30063x1 double]
%          wind: [30063x1 double]
%          date: [30063x1 double]
%
%
% WeatherCSUPower.mat: named 'Weather' in workspace
%
%      Called in NARX_fulltime for all weather variables
%
%      solar: [49334x1 double]
%      temp: [49334x1 double]
%      date: [49334x1 double]
%      RH: [49334x1 double]
% weekday: [1x1 struct]
% weekend: [1x1 struct]
%      wind: [49334x1 double]
%
%
%%      Data appended

%      Data can be appended to the current stuctures with the help of
%      .mat files in the 'Add_data' folder of the same directory.
%      -Read 'AA_Read_first.m'

%%      Energy Savings

%      'FortZedsavings.m' runs full 2011 analysis
%      - hour to be specified for one or two-hour scenario

%      This is currently setup for savings over the forecasted matrix of
%      'Forecast_final_4_14_2012.mat'

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% Forecaster for load period set by dates, weekdays
% created November 2011

% Inputs need to be in the format 'Day-Month-Year hour:minute:second'
% i.e. '01-Jul-2008 23:00:00'
% all months are abbreviated with first three letters

clear all
close all

% Define dates here (Period of prediction: July 1, 2006 to June 30, 2011)
startdatefc='09-Feb-2011 0:00:00'; % leave in this format, all months are
first three letters,
enddatefc='09-Feb-2011 23:00:00'; % hours must be left the same

```

```

load POWER_split.mat

load WEATHER_split.mat

pred_target=zeros(1,24);
pred_pred=zeros(1,24);
timevec=zeros(24,1);
startdate1=datevec(startdatefc);
enddate1=datevec(enddatefc);
weekday_find=find(S.weekday.date==datenum(startdate1));
holiday_find=find(S.weekend.date==datenum(startdate1));

% if weekday_find>0
%     disp('Occupied Day')
%     [targetSeriesVal ypred mape_wholenetwork day N net inputweekday
inputSeriesPred wind dayofwk] = NARX_occupied(startdatefc, enddatefc);

% else
%     disp('Unoccupied Day')
%     [targetSeriesVal ypred tvec N powerwkday net] =
NARX_unoccupied(startdatefc, enddatefc);
%
% end

% This section can be used to input these values into vectors created by
% Step_through_Predict...

pred_pred(1,1:24)=cell2mat(ypred);
pred_target(1,1:24)=cell2mat(targetSeriesVal);
mape=mape_wholenetwork;
day=datenum(day);
timevec(1)=day;

ypred=cell2mat(ypred);
tsv=cell2mat(targetSeriesVal);
difference=tsv-ypred;
disp('Mean Average Percent Error of Prediction')
mape_pred = mean(abs(difference./tsv*100)) % mean average
percent error
disp('Coefficient of Variance, Prediction')
CV=sqrt((1/N)*sum((ypred-tsv).^2))./mean(ypred)*100 % root mean
square
max_percenterror=max(abs(difference))/max(ypred)*100
%%
% clearvars -except startdatefc enddatefc

%% Forecaster for load period set by dates

% disp('_____')
% disp('Full data set used - Holiday Input vector')
%
% load CSUPower.mat
% load WeatherCSUPower.mat
%

```

```

%
% [targetSeriesVal ypred tvec N powerweekday net] = NARX_fulltime(startdatefc,
enddatefc);
% ypred=cell2mat(ypred);
% tsv=cell2mat(targetSeriesVal);
% difference=tsv-ypred;
% mape_pred = mean(abs(difference)./tsv*100) % mean
average percent error
% CV=sqrt((1/N)*sum((ypred-tsv).^2))./mean(ypred')*100 % root mean
square
% max_percenterror=max(abs(difference))/max(ypred)*100

```

ANN Function:

```

function [targetSeriesVal ypred mape_wholenetwork day N net inputweekday
inputSeriesPred wind dayofwk]=NARX_occupied(startdate,enddate)
% Run from Main_FC; creates inputs and targets for weekday NN

load POWER_split.mat
load WEATHER_split.mat

% These inputs are provided by Main_FC

startdate=datevec(startdate); % convert
input strings to vectors
enddate=datevec(enddate);
begin=S.weekday.date(1); % first date
for training data, this includes all data available
last1=find(S.weekday.date==datenum(startdate));
lasttest=find(S.weekday.date==datenum(enddate)); % finds last
date for prediction
last1=last1-1; % this is the
last point for the training (training ends at startdate-1)

last = S.weekday.date(lasttest);
dayofwk = weekday(S.weekday.date(1:lasttest));

if last1==0 % if
dates are not put in correctly or not in correct order
disp 'not in weekday sequence or dates entered incorrectly'
end

% this is the last point in the prediction
N=lasttest-last1; %points predicted
ahead of the 'last1'
tvec=S.weekday.date(1:lasttest); %unused, just a
check for dates referenced
hrvec1=S.weekday.hour(1:lasttest); %makes hour
vector from indices (hours are in matlab time, starting at 1 hour and ending
at 24)
time_predicted=datestr(S.weekday.date(last1+1:lasttest)) %prints time
period predicted
day=time_predicted(1,:);

```



```

% Use dates to get power from that time period
powerwkday=S.weekday.Power(1:lasttest); % creates power
vector from 1st day available to end of prediction variables, will be split
at line 77

b=find(T.weekday.date==datenum(begin)); %finds beginning date
in Weather structure
l=find(T.weekday.date==datenum(last)); %finds end date...

sun=T.weekday.sun(b:l); % solar
air=T.weekday.temp(b:l); % temp
relhum=T.weekday.relhum(b:l); % rel. humidity
wind=T.weekday.wind(b:l); % wind

% All input data is produced for the period between beginning of data set
% to end of prediction. The NN data prep splits this to use only the
% pre-prediction data to train and validate. The 'N', or number of points
% predicted, dictates how much is truncated at end of the data to be used
% only in the prediction function.

inputweekday=[sun, air, relhum, wind, dayofwk, hrvec1]; %This creates
a vector of all the input variables from 1st available training day
% to the last day of the prediction. This is done so that all data is
compiled in function 'tonndata'(line 71 and 72)the same way. The prediction
day will be
% chopped off at line 76 before training.

%%
% NARX Neural Network

%
% These variables must be defined:
%
% inputweekday - input time series.
% powerwkday - feedback time series.
% N - number of timesteps ahead to predict

input = tonndata(inputweekday,false,false);
target = tonndata(powerwkday,false,false);

% inputSeriesVal will be used for predicting new targets. targetSeriesVal
will be used for
% network validation after prediction

```

```

inputSeries = input(1:end-N);
targetSeries = target(1:end-N);           % inputs and targets
available for training

inputSeriesVal = input(end-N+1:end);

targetSeriesVal = target(end-N+1:end);     % This is theoretically not
available

% Create a NARXnet
delay=24;
inputDelays = 1:2;
feedbackDelays = 1:delay;

hiddenLayerSize = 20;                     % decided heuristically with
Hiddenlayer_loop.m
net = narxnet(inputDelays,feedbackDelays,hiddenLayerSize);

%%
% Choose Input and Feedback Pre/Post-Processing Functions
% Settings for feedback input are automatically applied to feedback output
% For a list of all processing functions type: help nnprocess
% Customize input parameters at: net.inputs{i}.processParam
% Customize output parameters at: net.outputs{i}.processParam
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};           %
Normalizes data to -1 to 1 range to
net.inputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Prepare the Data for Training and Simulation
% The function PREPARETS prepares timeseries data for a particular network,
% shifting time by the minimum amount to fill input states and layer states.
% Using PREPARETS allows you to keep your original time series data
unchanged, while
% easily customizing it for networks with differing numbers of delays, with
% open loop or closed loop feedback modes.
[inputs,inputStates,layerStates,targets] =
preparets(net,inputSeries,{},targetSeries);

% Setup Division of Data for Training, Validation, Testing
% The function DIVIDERAND randomly assigns target values to training,
% validation and test sets during training.
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand'; % Divide data randomly
% The property DIVIDEMODE set to TIMESTEP means that targets are divided
% into training, validation and test sets according to timesteps.
% For a list of data division modes type: help nntype_data_division_mode
net.divideMode = 'time'; % Divide up values by timestep
net.divideParam.trainRatio = 75/100;      % based on historical
success
net.divideParam.valRatio = 25/100;
% net.divideParam.testRatio = 15/100;

% Choose a Training Function
% For a list of all training functions type: help nntrain

```

```

% Customize training parameters at: net.trainParam
net.trainFcn = 'trainlm'; % Levenberg-Marquardt

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

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
% Customize plot parameters at: net.plotParam
net.plotFcns = {'plotperform','plottrainstate','plotresponse', ...
    'ploterrcorr', 'plotinerrcorr'};

% % Turn off the window
net.trainParam.showWindow = false;
net.trainParam.showCommandLine = false;

% Train the Network
[net,tr] = train(net,inputs,targets,inputStates,layerStates);

% Test the Network
outputs = net(inputs,inputStates,layerStates);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs);

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

% calculate the Mean average percent error for the test set
% resids=cellfun(@minus,outputs,testTargets);
% s=cell2mat(testTargets);
% s = s(~isnan(s));
% resids=resids(~isnan(resids));
% relative_error= resids./s;
% disp('Mean Average Percent Error of NN Test Points');
% mape_testpoints=mean(abs(relative_error)*100);
% error2=norm(relative_error,2);
% errorInf=norm(relative_error,inf);

% View the Network
% view(net)

% Plots
% Uncomment these lines to enable plots.
% Figure, plotperform(tr)
% Figure, plottrainstate(tr)
% Figure, plotregression(testTargets,outputs)
% Figure, plotresponse(targets,outputs)

```

```

% Figure, ploterrcorr(errors)
% Figure, plotinerrcorr(inputs,errors)

% Closed Loop Network
% Use this network to do multi-step prediction.
% The function CLOSELOOP replaces the feedback input with a direct
% connection from the output layer.
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];

% view(netc)
% [xc,xic,aic,tc] = preparets(netc,inputSeries,{},targetSeries);
% yc = netc(xc,xic,aic);
% closedLoopPerformance = perform(netc,tc,yc)

%

% % Early Prediction Network
% % For some applications it helps to get the prediction a timestep early.
% % The original network returns predicted y(t+1) at the same time it is
% % given y(t+1).
% % For some applications such as decision making, it would help to have
% % predicted
% % y(t+1) once y(t) is available, but before the actual y(t+1) occurs.
% % The network can be made to return its output a timestep early by removing
% % one delay
% % so that its minimal tap delay is now 0 instead of 1. The new network
% % returns the
% % same outputs as the original network, but outputs are shifted left one
% % timestep.
% nets = removedelay(net);
% nets.name = [net.name ' - Predict One Step Ahead'];
% view(nets)
% [xs,xis,ais,ts] = preparets(nets,inputSeries,{},targetSeries);
% ys = nets(xs,xis,ais);
% earlyPredictPerformance = perform(nets,ts,ys)

% Checks MAPE of whole network

ypred1=sim(net,inputs);
residuals=cellfun(@minus,targets,ypred1);
r=cell2mat(targets);

mape_wholenetwork=nanmean(abs(residuals./r*100));

% %%
%
% % This uses inputSeriesPred and targetSeriesPred as initial loading in the
% % closed loop
%
inputSeriesPred = [inputSeries(end-delay+1:end),inputSeriesVal];
%matrix of last N points in training inputs, and the inputs to prediction

```

```

% only 'inputDelays' (line 85) of the last inputSeries is used for prediction
inputs
targetSeriesPred = [targetSeries(end-delay+1:end), con2seq(nan(1,N))];

[Xs,Xi,Ai,Ts] = preparets(netc,inputSeriesPred,{},targetSeriesPred);

ypred=netc(Xs,Xi,Ai);

% perf = perform(net,ypred,targetSeriesVal);

% Figure(5)
%
% plot(cell2mat(ypred),'', 'DisplayName', 'Network
Predictions', 'YDataSource', 'f');hold
all;plot(cell2mat(targetSeriesVal),'', 'DisplayName', 'Expected
KWs', 'YDataSource', 'ypred');hold off;Figure(gcf);
%
% plot([nan(1,length(targetSeriesVal)),cell2mat(ypred);
%      nan(1,length(targetSeriesVal)),(targetSeriesVal)'])
%
% legend('Network Predictions','Expected Outputs', 'Location','Northwest')
% title('Occupied Day Prediction - Split Data')
% %
end

```

Holidays that are excluded from forecasting, not including weekends:

```

% Finds specified dates and fills in zero vector with 1's on those dates.
% this should be run to create a vector of 'z' which has 0's where it is
% not a holiday. Then replace CSUPower.mat structure 'C' with z and run
% through 'Weeksplit.m' make sure to resave new C structure in CSUPower.mat

```

```

clear all
close all

```

```

load CSUPower.mat

```

```

z=zeros(size(C.fulltime));

```

```

a=datetime([2006 9 1 1 0 0]); % labor day 2006
a=find(C.fulltime==a);
b=datetime([2006 9 1 23 0 0]);
b=find(C.fulltime==b);
z(a:b)=1;

```

```

c=datetime([2006 11 20 0 0 0]); % thanksgiving 2006
c=find(C.fulltime==c);
d=datetime([2006 11 24 23 0 0]);

```

```

d=find(C.fulltime==d);
z(c:d)=1;

e=datetime([2006 12 20 0 0 0]);           % Christmas break
e=find(C.fulltime==e);
f=datetime([2006 12 27 23 0 0]);
f=find(C.fulltime==f);
z(e:f)=1;

g=datetime([2006 12 29 0 0 0]);
g=find(C.fulltime==g);
h=datetime([2007 1 1 23 0 0]);
h=find(C.fulltime==h);
z(g:h)=1;

i=datetime([2007 1 15 0 0 0]);
i=find(C.fulltime==i);
j=datetime([2007 1 15 23 0 0]);
j=find(C.fulltime==j);
z(i:j)=1;

k=datetime([2007 3 12 0 0 0]);
k=find(C.fulltime==k);
l=datetime([2007 3 16 23 0 0]);
l=find(C.fulltime==l);
z(k:l)=1;

m=datetime([2007 5 28 0 0 0]);
m=find(C.fulltime==m);
n=datetime([2007 5 28 23 0 0]);
n=find(C.fulltime==n);
z(m:n)=1;

o=datetime([2007 7 4 0 0 0]);           % July 4 2007
o=find(C.fulltime==o);
p=datetime([2007 7 23 0 0 0]);
p=find(C.fulltime==p);
z(o:p)=1;

q=datetime([2007 9 3 0 0 0]);
q=find(C.fulltime==q);
r=datetime([2007 9 3 23 0 0]);
r=find(C.fulltime==r);
z(q:r)=1;

s=datetime([2007 11 19 0 0 0]);
s=find(C.fulltime==s);
t=datetime([2007 11 23 23 0 0]);
t=find(C.fulltime==t);
z(s:t)=1;

u=datetime([2007 12 24 0 0 0]);
u=find(C.fulltime==u);
v=datetime([2007 12 27 23 0 0]);
v=find(C.fulltime==v);

```

```

z(u:v)=1;

w=datetime([2007 12 31 0 0 0]);
w=find(C.fulltime==w);
x=datetime([2008 1 1 23 0 0]);
x=find(C.fulltime==x);
z(w:x)=1;

y=datetime([2008 1 21 0 0 0]);
y=find(C.fulltime==y);
aa=datetime([2008 1 21 23 0 0]);
aa=find(C.fulltime==aa);
z(y:aa)=1;

bb=datetime([2008 3 17 0 0 0]);
bb=find(C.fulltime==bb);
cc=datetime([2008 3 21 0 0 0]);
cc=find(C.fulltime==cc);
z(bb:cc)=1;

dd=datetime([2008 5 26 0 0 0]);
dd=find(C.fulltime==dd);
ee=datetime([2008 5 26 23 0 0]);
ee=find(C.fulltime==ee);
z(dd:ee)=1;

ff=datetime([2008 7 4 0 0 0]);
ff=find(C.fulltime==ff);
gg=datetime([2008 7 4 23 0 0]);
gg=find(C.fulltime==gg);
z(ff:gg)=1;

hh=datetime([2008 9 1 0 0 0]);
hh=find(C.fulltime==hh);
ii=datetime([2008 9 1 23 0 0]);
ii=find(C.fulltime==ii);
z(hh:ii)=1;

jj=datetime([2008 11 22 0 0 0]);
jj=find(C.fulltime==jj);
kk=datetime([2008 11 28 0 0 0]);
kk=find(C.fulltime==kk);
z(jj:kk)=1;

ll=datetime([2008 12 24 0 0 0]);
ll=find(C.fulltime==ll);
mm=datetime([2008 12 27 23 0 0]);
mm=find(C.fulltime==mm);
z(ll:mm)=1;

nn=datetime([2009 1 1 0 0 0]);
nn=find(C.fulltime==nn);
pp=datetime([2009 1 2 23 0 0]);
pp=find(C.fulltime==pp);
z(nn:pp)=1;

```

```

qq=datenum([2009 3 16 0 0 0]);
qq=find(C.fulltime==qq);
rr=datenum([2009 3 20 23 0 0]);
rr=find(C.fulltime==rr);
z(qq:rr)=1;

ss=datenum([2009 5 25 0 0 0]);
ss=find(C.fulltime==ss);
tt=datenum([2009 5 25 23 0 0]);
tt=find(C.fulltime==tt);
z(ss:tt)=1;

uu=datenum([2009 7 3 0 0 0]);
uu=find(C.fulltime==uu);
vv=datenum([2009 7 3 23 0 0]);
vv=find(C.fulltime==vv);
z(uu:vv)=1;

ww=datenum([2009 9 7 0 0 0]);
ww=find(C.fulltime==ww);
xx=datenum([2009 9 7 23 0 0]);
xx=find(C.fulltime==xx);
z(ww:xx)=1;

yy=datenum([2009 11 23 0 0 0]);
yy=find(C.fulltime==yy);
aaa=datenum([2009 11 27 23 0 0]);
aaa=find(C.fulltime==aaa);
z(yy:aaa)=1;

bbb=datenum([2009 12 23 0 0 0]);
bbb=find(C.fulltime==bbb);
ccc=datenum([2009 12 25 23 0 0]);
ccc=find(C.fulltime==ccc);
z(bbb:ccc)=1;

ddd=datenum([2010 1 1 0 0 0]);
ddd=find(C.fulltime==ddd);
eee=datenum([2010 1 1 23 0 0]);
eee=find(C.fulltime==eee);
z(ddd:eee)=1;

fff=datenum([2010 3 15 0 0 0]);
fff=find(C.fulltime==fff);
ggg=datenum([2010 3 19 23 0 0]);
ggg=find(C.fulltime==ggg);
z(fff:ggg)=1;

hhh=datenum([2010 7 5 0 0 0]);
hhh=find(C.fulltime==hhh);
iii=datenum([2010 7 5 23 0 0]);
iii=find(C.fulltime==iii);
z(hhh:iii)=1;

```



```

jjj=datenum([2010 9 6 0 0 0]);
jjj=find(C.fulltime==jjj);
kkk=datenum([2010 9 6 23 0 0]);
kkk=find(C.fulltime==kkk);
z(jjj:kkk)=1;

l11=datenum ([2010 11 22 0 0 0]);
l11=find(C.fulltime==l11);
mmm=datenum([2010 11 26 23 0 0]);
mmm=find(C.fulltime==mmm);
z(l11:mmm)=1;

nnn=datenum([2010 12 20 0 0 0]);
nnn=find(C.fulltime==nnn);
ooo=datenum([2010 12 24 23 0 0]);
ooo=find(C.fulltime==ooo);
z(nnn:ooo)=1;

ppp=datenum([2010 12 31 0 0 0]);
ppp=find(C.fulltime==ppp);
qqq=datenum([2010 12 31 23 0 0]);
qqq=find(C.fulltime==qqq);
z(ppp:qqq)=1;

rrr=datenum([2011 1 17 0 0 0]);
rrr=find(C.fulltime==rrr);
sss=datenum([2011 1 17 23 0 0]);
sss=find(C.fulltime==sss);
z(rrr:sss)=1;

%MLK Day 2011

ttt=datenum([2011 3 14 0 0 0]);
ttt=find(C.fulltime==ttt);
uuu=datenum([2011 3 18 23 0 0]);
uuu=find(C.fulltime==uuu);
z(ttt:uuu)=1;

%Spring Break 2011

vvv=datenum([2011 5 30 0 0 0]);
vvv=find(C.fulltime==vvv);
www=datenum([2011 5 30 23 0 0]);
www=find(C.fulltime==www);
z(vvv:www)=1;

%Misc. Univ. Holiday

yyy=datenum([2011 2 1 0 0 0]);
outlier (power outage)
yyy=find(C.fulltime==yyy);
xxx=datenum([2011 2 1 23 0 0]);
xxx=find(C.fulltime==xxx);
z(yyy:xxx)=1;

% This day is an obvious

aaaa=datenum([2011 7 4 0 0 0]);
aaaa=find(C.fulltime==aaaa);
bbbb=datenum([2011 7 4 23 0 0]);
bbbb=find(C.fulltime==bbbb);
z(aaaa:bbbb)=1;

%Misc. Univ. holiday

```

```

cccc=datetime([2011 9 5 0 0 0]);           %misc univ holiday
cccc=find(C.fulltime==cccc);
dddd=datetime([2011 9 5 23 0 0]);
dddd=find(C.fulltime==dddd);
z(cccc:dddd)=1;

eeee=datetime([2011 11 21 0 0 0]);         %fall break/thanksgiving
eeee=find(C.fulltime==eeee);
ffff=datetime([2011 11 25 23 0 0]);
ffff=find(C.fulltime==ffff);
z(eeee:ffff)=1;

gggg=datetime([2011 12 23 0 0 0]);         %winter break 2011
gggg=find(C.fulltime==gggg);
hhhh=datetime([2011 12 28 23 0 0]);
hhhh=find(C.fulltime==hhhh);
z(gggg:hhhh)=1;

```

Savings Algorithm:

```

close all
clear all
%% Calculates the savings in energy and cost based on the definition of
'hours'

load CSUPower.mat
load Forecast_final_4_14_2012.mat

%% Choose a savings scenario of one hour run time or two hour runtime
(options: 1 or 2)
hours=2;

for p=1:12;
Month=p;                               % Month predicted, only 1,2,6,7 allowed right
now;
% Day=5;                               % This has to be a day that was included in
"occupied days" in the predictions, stick to weekdays in late JAN. and all
weekdays in FEB.

% plot this day separate
% specific_day=28;
% one=299;                             % amt. of unloadable on feeder one
% four=100;                             % amount of load off of feeder four
% both=four+one;
% feeder=both;

% this loop cycles through all days in the month

for k=1:31
    Day=k;

```

```

u=find(BE.first.date==datenum([2011 Month Day 0 0 0]));

if u>0
    %disp('Occupied Day')
    [facpeak_savings projected_energycostsavings energy_savings
    energycost_savings coinpeaksavings real newreal newvec
    pred]=savingsonehour(Month, Day, u,k, hours);
    energy_savings_total(k,1)=energy_savings;
    energycost_savings_total(k,1)=energycost_savings;
    projected_energycost_savings_total(k,1)=projected_energycostsavings;
    coinpeaksavings_total(k,1)=coinpeaksavings;
    facpeak_save(k,1)=facpeak_savings;
    newrealmat(k,1:24)=newreal;
    newvecmat(k,1:24)=newvec;
    predmat(k,1:24)=pred;
else
    %disp('Unoccupied Day')
end

end

s=find(energycost_savings_total<0); %find and change
negative savings(not possible to increase load if we are only turning things
off)
energycost_savings_total(s)=0;
x=find(coinpeaksavings_total<0);
coinpeaksavings_total(x)=0;
total_monthly_savings=sum(energycost_savings_total)+sum(coinpeaksavings_total
)+sum(facpeak_save);
z=find(energy_savings_total<0);
energy_savings_total(z)=0;
average_energy_savings=mean(energy_savings_total);
y=find(projected_energycostsavings<0);
projected_energycostsavings(y)=0;
total_projectedcostsavings=sum(projected_energycost_savings_total)+sum(coinpe
aksavings_total)+sum(facpeak_save);

COST_ENERGY(p,1)=average_energy_savings;
COST_ENERGY(p,2)=sum(energycost_savings_total);
COST_ENERGY(p,4)=sum(coinpeaksavings_total);
COST_ENERGY(p,5)=total_projectedcostsavings;
COST_ENERGY(p,6)=total_monthly_savings;
COST_ENERGY(p,3)=sum(facpeak_save);

end

% Figure (2)
% plot(newrealmat(specific_day,:), 'c');hold
on;plot(newvecmat(specific_day,:), 'r'); hold on;

```

```

plot(predmat(specific_day,1:24),'g'); hold
on;plot(facilitypeak(specific_day,1:24),'b')
% legend('Final','Pred minus load','Forecast','Unchanged target',2)

```

Remaking load profiles based on savings :

```

function [facpeak_savings projected_energycostsavings energy_savings
energycost_savings coinpeaksavings real newreal newvec pred] =
savingsonehour(Month, Day,u,k, hours)
% savingsonehour.m function which routes energy saving scenario to one or
% two hour, and calculates the savings for that particular code.

% This function designates the expected peak and expected length via
% the Month assigned in FortZed according to the graph of coincident peak

load CSUPower.mat
load Forecast_final_3_28.mat

% determines month, peak, and time changed, unload is a vector that starts
% at the first probable hour for peak, and is as long as tmax (the length
% of the vector spans all probable hours for peak)
if hours==1
[peakvec unload tmax energycost cpeak ] = onehour(Month);
elseif hours==2
[peakvec unload tmax energycost cpeak ] = twohour(Month);
end

% dates=BE.first.date(u:u+23);
pred=BE.average.prediction.KW(u,:)';
u=find(BE.first.date==datenum([2011 Month Day 0 0 0]));
real=BE.first.target.KW(u,:)';
peakvec=peakvec+1; % time starts at zero so
peakvec time is hour+1 indices
cpeak=cpeak+1; % HOUR 0 is at cell 1, so
this converts peak times to cell # in vector

% find minimum load for day, subtract from load profile
f=pred-min(pred);

morning=f(1:peakvec-1); % this gives the vector from
midnight to peakvec-1 of predicted load
realmorn=real(1:peakvec-1);
peakshave=zeros(tmax,1);

% for i=1:4
% peakshave(i,1)=0.7*f(peak-1+i);
% end

```

```

for i=1:tmax
    peakshave(i,1)=f(peakvec-1+i)-unload(i);
end

for j=1:tmax
    peakshavereal(j,1)=real(peakvec-1+j)-unload(j);
end

afternoon=f(peakvec+tmax:end);
realaft=real(peakvec+tmax:end);

new=[morning; peakshave; afternoon];
newvec=new+min(pred);
newreal=[realmorn; peakshavereal; realaft];

% subplot(6,6,k)
%
% %newreal: energysavings off of real, calculated from prediction
% %real: target
% %pred: ANN forecast
% %newvec: profile created from energysavings off of forecasted
%
% plot(newreal,'c'); hold on; plot(real,'b'); hold on; plot(pred,'g'); hold
on; plot(newvec,'r')
% set(gca,'xtick',[],'ytick',[])
% line([cpeak,cpeak],[8000,14000])
% legend('Saving','Target','Predicted',2)

% find coin. peak savings(in %/kW MORE) for the day, if not coin. peak,
savings is zero
[coincost]=coinpeak(Month, Day);
[facpeak_savings]=facilitypeak(Month, Day, real, newreal);

energynew=sum(newvec); % energy from new
vector of 4 hours 30% drop in load
realenergynew=sum(newreal);
energyold=sum(real); % energy from actual
energy
energy_savings=(1-realenergynew/energyold)*100;
energycost_savings=(energyold-realenergynew)*energycost;
pred_energyold=sum(pred);
projected_energycostsavings=(pred_energyold-energynew)*energycost;

coinpeaksavings=(real(cpeak)-newreal(cpeak))*coincost; % $10.20
is the cost associated with one more kilowatt during coincident hour
format shortg

```

```
total_bling_savings=coinpeaksavings+energycost_savings;
```

```
end
```

One hour savings:

```
function [ peakvec unload tmax energycost cpeak ] = onehour( Month )
%unload.m Makes a vector called unload which turns off loads based on the
%months coincident peak probabilities
%
one=299;           %Feeder one
four=100;          %Feeder four
both=399;

summer=0.0367;     % energy demand rate for summer and winter
winter=0.0349;

if Month==01

    peakvec=18;
    cpeak=18;
    tmax=1;
    unload=both;    % Unload is a vector which "turns off" load
based on the hour
    energycost=winter; % .0349 is the cost associated with
additional KWh during winter
elseif Month==02

    peakvec=18;
    cpeak=18;
    tmax=1;
    unload=both;    % Unload is a vector which "turns off" load
based on the hour
    energycost=winter;
elseif Month==03

    peakvec=18;
    cpeak=18;
    tmax=2;
    unload(1)=one;
    unload(2)=four;
    energycost=winter;
elseif Month==04

    peakvec=14;
    cpeak=19;
    tmax=7;
    unload(1)=both;
    unload(2)=0;
    unload(3)=0;
    unload(4)=0;
```

```

        unload(5)=0;
        unload(6)=one;
        unload(7)=four;
        energycost=winter;
elseif Month==05

        peakvec=14;
        cpeak=14;
        tmax=4;
        unload(1)=both;
        unload(2)=0;
        unload(3)=one;
        unload(4)=four;
        energycost=winter;
elseif Month==06

        peakvec=16;
        cpeak=17;
        tmax=2;
        unload(1)=one;
        unload(2)=four;
        energycost=summer;
additional KWh during winter % .0367 is the cost associated with
elseif Month==07

        peakvec=15;
        cpeak=17;
        tmax=3;
        unload(1)=four;
        unload(2)=one;
        unload(3)=four;
        energycost=summer;
elseif Month==8

        peakvec=14;
        cpeak=15;
        tmax=4;
        unload(1)=one;
        unload(2)=four;
        unload(3)=one;
        unload(4)=four;
        energycost=summer;
elseif Month==9

        peakvec=14;
        cpeak=16;
        tmax=4;
        unload(1)=four;
        unload(2)=one;
        unload(3)=four;
        unload(4)=one;
        energycost=winter;
elseif Month==10

        peakvec=16;
        cpeak=16;

```

```

    tmax=4;
    unload(1)=both;
    unload(2)=0;
    unload(3)=four;
    unload(4)=one;
    energycost=winter;
elseif Month==11

    peakvec=17;
    cpeak=18;
    tmax=2;
    unload(1)=one;
    unload(2)=four;
    energycost=winter;
elseif Month==12

    peakvec=17;
    cpeak=17;
    tmax=2;
    unload(1)=one;
    unload(2)=four;
    energycost=winter;
end
end

```

Two hour savings:

```

function [ peakvec unload tmax energycost cpeak ] = twohour( Month )
%unload.m Makes a vector called unload which turns off loads based on the
%months coincident peak probabilities
% Detailed explanation goes here

one=299;           %Feeder one
four=100;          %Feeder four
both=399;

summer=0.0367;     % energy demand rate for summer and winter
winter=0.0349;

if Month==01

    peakvec=18;
    cpeak=18;
    tmax=1;
    unload=both;    % Unload is a vector which "turns off" load
based on the hour
    energycost=winter; % .0349 is the cost associated with
additional KWh during winter
elseif Month==02

    peakvec=18;
    cpeak=18;
    tmax=1;

```



```

        unload=both;                                % Unload is a vector which "turns off" load
based on the hour
        energycost=winter;
elseif Month==03

        peakvec=18;
        cpeak=18;
        tmax=2;
        unload(1)=both;
        unload(2)=both;
        energycost=winter;
elseif Month==04

        peakvec=14;
        cpeak=19;
        tmax=7;
        unload(1)=both;
        unload(2)=0;
        unload(3)=0;
        unload(4)=0;
        unload(5)=0;
        unload(6)=both;
        unload(7)=both;
        energycost=winter;
elseif Month==05

        peakvec=14;
        cpeak=14;
        tmax=4;
        unload(1)=both;
        unload(2)=0;
        unload(3)=both;
        unload(4)=both;
        energycost=winter;
elseif Month==06

        peakvec=16;
        cpeak=17;
        tmax=2;
        unload(1)=both;
        unload(2)=both;
        energycost=summer;                                % .0367 is the cost associated with
additional KWh during winter
elseif Month==07

        peakvec=15;
        cpeak=17;
        tmax=3;
        unload(1)=four;
        unload(2)=both;
        unload(3)=one;
        energycost=summer;
elseif Month==8

        peakvec=14;
        cpeak=15;

```

```

    tmax=4;
    unload(1)=one;
    unload(2)=four;
    unload(3)=both;
    unload(4)=one;
    energycost=summer;
elseif Month==9

    peakvec=14;
    cpeak=16;
    tmax=4;
    unload(1)=four;
    unload(2)=both;
    unload(3)=one;
    unload(4)=four;
    energycost=winter;
elseif Month==10

    peakvec=16;
    cpeak=16;
    tmax=4;
    unload(1)=both;
    unload(2)=0;
    unload(3)=both;
    unload(4)=both;
    energycost=winter;
elseif Month==11

    peakvec=17;
    cpeak=18;
    tmax=2;
    unload(1)=both;
    unload(2)=both;
    energycost=winter;
elseif Month==12

    peakvec=17;
    cpeak=17;
    tmax=2;
    unload(1)=both;
    unload(2)=both;
    energycost=winter;
end
end

```

APPENDIX B

Details of VFD assets utilized for simulation in this thesis.

Location	Percent reduction	kW savings
NESB; VFD-22; MFG ROBICON; SERVES AHU-1; LOCATION BASEMENT; 100HP; 480VOLT; ID-PWM; INSTALLED 1993	25%	35
NESB; VFD-21; MFG ROBICON; SERVES RF-2; LOCATION BASEMENT; 15HP; 480VOLT; ID454; INSTALLED 1993	25%	5
NESB; VFD-23; MFG ROBICON; SERVES AHU-2; LOCATION BASEMENT; 100HP; 480VOLT; ID-PWM; INSTALLED 1993	25%	35
NESB; VFD-20; MFG ROBICON; SERVES RF-1; LOCATION BASEMENT; 15HP; 480VOLT; ID454; INSTALLED 1993	25%	5
COMPUTER SCIENCE ;VFD3;AHU1;SF; 40HP;480V;MFG ABB;ROOFTOP UNIT;	25%	14
COMPUTER SCIENCE ;VFD4;AHU1;RF; 15HP;480V;MFG ABB;ROOFTOP UNIT;	25%	5
COMPUTER SCIENCE ;VFD1;AHU2;RF; 15HP;480V;MFG ABB;ROOFTOP UNIT;	25%	5
COMPUTER SCIENCE ;VFD2;AHU2;SF; 40HP;480V;MFG ABB;ROOFTOP UNIT;	25%	14
NATURAL RESOURCES; VFD-43; MFG ABB ACH400 SERVES; DD-1; LOCATION; NW BASEMENT ELEC ROOM 100HP; 460VOLT; INSTALLED 2000?	25%	35
NATURAL RESOURCES; VFD-44; MFG ABB ACH400SERVES; DD-2; LOCATION; NW BASEMENT ELEC ROOM 100HP; 460VOLT; INSTALLED 2000?	25%	35
NATURAL RESOURCES; VFD-45; MFG ABB ACH550 SERVES; DD-2 RETURN FAN RF2; LOCATION; NW BASEMENT ELEC ROOM 15HP; 460VOLT; INSTALLED 2000?	25%	5
NATURAL RESOURCES; VFD-46; MFG ABB ACH550 SERVES; DD-1 RETURN FAN 1; LOCATION; NW BASEMENT ELEC ROOM 25HP; 460VOLT; INSTALLED 2000?	25%	9
CLARK; VFD-32; MFG ABB ; SERVES FE-25 LOCATION PENTHOUSE A WING; 3HP; 208VOLT; ESP-130 INSTALLED 2007;	25%	1
CLARK; VFD-33; MFG ABB; SERVES F-10 LOCATION PENTHOUSE A WING; 20HP; 208VOLT; ESP-130 INSTALLED 2007;	25%	7
CLARK; VFD-119; MFG ABB; SERVES F-4 LOCATION PENTHOUSE C WING; 25HP; 460VOLT; VTAC111 INSTALLED 2007;	25%	9
CLARK; MFG ABB; SERVES F-4 LOCATION PENTHOUSE C WING; 3HP; 460VOLT; VTAC111 INSTALLED 2007;	25%	1
CLARK; VFD-34; MFG ABB; SERVES FE-24 LOCATION PENTHOUSE A WING; 5HP; 208VOLT; ESP-130 INSTALLED 2007;	25%	2
CLARK; VFD-42; MFG ABB; SERVES F-3 LOCATION PENTHOUSE C WING; 15HP; 460VOLT; VTAC111 INSTALLED 2007;	25%	5
CLARK; MFG ABB; SERVES F-3 LOCATION PENTHOUSE C WING; 2HP; 460VOLT; VTAC111 INSTALLED 2007;	25%	1
CLARK; VFD-41; MFG ABB; SERVES F-2 LOCATION PENTHOUSE C WING; 15HP; 460VOLT; VTAC111 INSTALLED 2007	25%	5
CLARK; MFG ABB; SERVES F-2 LOCATION PENTHOUSE C WING; 3HP; 460VOLT; VTAC111 INSTALLED 2008	25%	1
CLARK; VFD-35; MFG ABB; SERVES FE-23 LOCATION PENTHOUSE A WING; 3HP; 208VOLT; E-3 INSTALLED 2007;	25%	1

CLARK; VFD-36; MFG ABB; SERVES F-9 LOCATION PENTHOUSE A WING; 30HP; 208VOLT; ESP-130 INSTALLED 2007;	25%	10
CLARK; VFD-40; MFG ABB; SERVES F-1 LOCATION PENTHOUSE C WING; 25HP; 460VOLT; VTAC111 INSTALLED 2007;	25%	9
CLARK; MFG ABB; SERVES F-1 LOCATION PENTHOUSE C WING; 3HP; 460VOLT; VTAC111 INSTALLED 2007;	25%	1
CLARK; VFD-39; MFG ABB; SERVES FE-22 LOCATION PENTHOUSE A WING; 3HP; 208VOLT; ESP-130 INSTALLED 2007;	25%	1
CLARK;; MFG ABB; SERVES F-7 LOCATION PENTHOUSE A WING; 30HP; 208VOLT; ESP-130 INSTALLED 2007;	25%	10
CLARK; VFD-38; MFG ABB; CHW BLDG PUMP; LOCATION PENTHOUSE C WING; 20HP; 460VOLT; ESP-130 INSTALLED 2007;	25%	7
CLARK; VFD-37; MFG TOSHIBA; SERVES F-8 LOCATION PENTHOUSE A WING; 30HP; 208VOLT; ESP-130 INSTALLED 2007;	25%	10
ENGINEERING ;AHU4;SF; 50HP;480V;MFG GRAHAM VLT3500;ROOFTOP UNIT;	25%	17
ENGINEERING ;AHU4;RF; 15HP;480V;MFG GRAHAM VLT3500;ROOFTOP UNIT;	25%	5
ENGINEERING ;AHU3;SF; 40HP;480V;MFG ABB ACH550;ROOFTOP UNIT;	25%	14
ENGINEERING ;AHU3;RF; 15HP;480V;MFG ABB ACH550;ROOFTOP UNIT;	25%	5
ENGINEERING ;AHU2;SF; 40HP;480V;MFG GRAHAM VLT3500;ROOFTOP UNIT;	25%	14
ENGINEERING ;AHU2;RF; 7.5HP;480V;MFG GRAHAM VLT3500;ROOFTOP UNIT;	25%	3
ENGINEERING ;AHU1;SF; 40HP;480V;MFG GRAHAM VLT3500;ROOFTOP UNIT;	25%	14
ENGINEERING ;AHU1;RF; 10HP;480V;MFG GRAHAM VLT3500;ROOFTOP UNIT;	25%	3
ENGINEERING ;AHU5;SF; 25HP;480V;MFG VLT3500;ROOFTOP UNIT;	25%	9
ENGINEERING ;AHU5;RF; 10HP;480V;MFG GRAHAM VLT3500;ROOFTOP UNIT;	25%	3
Supply and return air fans	25%	16
COMPUTER SCIENCE; VFD-5;BLDG HW PUMP P-5: BASEMENT RM-02: MFG SQUARE D:480VOLT:5HP	25%	2
COMPUTER SCIENCE; VFD-4;BLDG HW PUMP P-4: BASEMENT RM-02: MFG SQUARE D:480 VOLT:5HP	25%	2
COMPUTER SCIENCE; VFD-3;DISTRICT CHW PUMP P-3: BASEMENT RM-04: MFG SQUARE D:480 VOLT:2HP	25%	1
COMPUTER SCIENCE; VFD-1;BLDG CHW PUMP P-1: BASEMENT RM-04: MFG SQUARE D:480 VOLT:5HP	25%	2
COMPUTER SCIENCE; VFD-2;BLDG CHW PUMP P-2: BASEMENT RM-04: MFG SQUARE D:480 VOLT:5HP	25%	2
WAGAR ;AHU101;SF; 3HP;208V;MFG ABB ACH550;1ST FLOOR MECH ROOM	25%	1
WAGAR ;AHU001; 7.5HP;208V;MFG DANFOSS VLT2800;BASEMENT WEST WING MECH ROOM	25%	3