VOLTAGE PROFILE ESTIMATION AND REACTIVE POWER CONTROL OF DISTRIBUTION FEEDERS

by

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Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

May 2008

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to my graduate committee for the time and assistance they provided in the completion of this dissertation. I am fortunate to have taken many excellent courses from Dr. William E. Dillon, Dr. Raymond R. Shoults, Dr. Kai-Shing Yueng, and Dr. Wei-Jen Lee. I am especially grateful to Dr. Dillon for his guidance and our many discussions during my graduate program. My thanks extend to Dr. Hua-Mei Chen for his review of my dissertation and participation on my committee. In particular, I want to express my appreciation and thanks to my supervising professor, Dr. Wei-Jen Lee. Dr. Lee's enthusiasm and expert knowledge make him an exceptional mentor and I highly value my time with him at the ESRC.

Many thanks go to the people at Oncor Electric Delivery including William E. Muston, Frank Daniel, Thomas Anthony, Larry Kohrmann, Alan Bern, and Ron Shipman for their assistance throughout the duration of my graduate project.

Finally, this dissertation would never have been possible without the love and encouragement that my family has given me throughout my life. I want to thank my sister Carol for being a positive example of academic excellence. A special thank you goes to my parents, Gerald and Tessa, for their advice, patience, and support during my academic education.

April 18, 2008

ABSTRACT

VOLTAGE PROFILE ESTIMATION AND REACTIVE POWER CONTROL

OF DISTRIBUTION FEEDERS

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The University of Texas at Arlington, 2008

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Distribution systems are important transportation links for the delivery of electric power. Understanding the system conditions of distribution feeders is vital for controlling power systems and maintaining electricity flow on power grids. With better knowledge of the system conditions on distribution feeders, a deliberate and systematic approach can be taken to achieve more efficient and reliable power delivery. Furthermore, better understanding of system conditions can be useful in reducing operation and maintenance costs in various power system applications such as voltage control and capacitor bank switching.

This dissertation presents a novel method for estimating the voltage profile of a radial distribution feeder using forecasted load demands and a three-phase power flow program. Additionally, using the forecasted system load and voltage estimations, an

efficient proactive capacitor bank switching algorithm has been developed to control the capacitor banks on distribution feeders.

The results of a comprehensive study of the effects of the short-term load forecasting software, the voltage profile estimation algorithm, and the capacitor switching algorithm are displayed in this dissertation. The topics presented in this dissertation include artificial neural networks for short-term feeder load forecasting, voltage profile estimation using three-phase power flows, capacitor bank switching for voltage improvement, and capacitor bank switching for switching reduction.

A software package based on the dissertation's research has been developed for electric delivery companies as a planning and operating tool for use in a distribution management system. The software package offers the electric delivery company the ability to estimate system load and voltage conditions on distribution feeders as well as control the feeder's capacitor banks in a more intelligent and coordinated manner. Future integration will allow the software to function as an autonomous component in the distribution management system.

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CHAPTER 1

INTRODUCTION

1.1 Background

The electric power system is one of the most important infrastructures in the modern era. Industry, commerce, and residential life all depend on the reliable supply of electric power. Efficiently managing the distribution systems that deliver power to the end user have grown in importance as more reliable and better quality of power are required for modern electrical devices. As more electrical devices and end users of electricity are served from the electric power system, the complexity of managing the resources on the distribution system increases and more intelligent monitoring and control of the distribution system becomes necessary. Furthermore, as experienced staff is retiring and comprehensive knowledge about asset management is decreasing, automation is becoming more important in the design and operation of future distribution systems.

Effective automation and control of a distribution system requires knowledge of the distribution system's load and voltage conditions. Monitoring the voltages at each load location along a distribution feeder can ensure that the electric service quality and system reliability are maintained at acceptable levels. However, at the present time, economic constraints limit widespread deployment of monitoring equipment on every load bus. Presently only a small number of voltage monitoring devices are available on the distribution lines. In addition to the economic concerns, retrieving and storing large amounts of data through a power system's communications network can be a technological challenge and in some situations a misuse of limited communication resources. These economic and technological problems associated with monitoring the system conditions must be addressed in order to have a flexible, efficient, and economically feasible distribution management system.

Another part of the distribution system where automation is desirable is in the area of capacitor bank switching. Traditionally, fixed capacitor banks or switched capacitor banks that contain locally controllers have been the most commonly deployed reactive power compensators on distribution systems due to their low cost and ease of installation. Most local controlled capacitor banks on the distribution system are switched online in a reactionary manner where the compensation is supplied only after the problem has occurred. Since the locally controlled capacitor banks only monitor their immediate area, without proper coordination of other compensation resources, this reactionary behavior can lead to an improper amount of compensation being switched online. The excessive compensation can lead to overvoltage on the distribution feeder as well as other power quality issues. The capacitor banks must then readjust their settings until the desired voltage is attained. This regular readjustment can lead to frequent switching of the capacitor banks than is necessary. The more times the capacitor banks are switched online and offline means that more maintenance of the capacitor banks is necessary since the switching contacts and controller can degrade with each operation. A reduction in the amount of switching can save maintenance costs and extend the useful lifetime of the capacitor banks.

At present, most utilities use predetermined switching sequences to connect and disconnect externally controlled capacitor banks along the distribution feeder. Although this scheme is straightforward, it has inherent drawbacks due to the lack of flexibility to accommodate dynamic load changes, long-term load growth, and possible feeder reconfigurations. However, as the cost of remotely switched capacitor banks and their associated infrastructure becomes more competitive with fixed and locally controlled capacitor banks, more remote controllable capacitor banks will be deployed on the distribution system. Through knowledge of the feeder's voltage profile and loading conditions, a central distribution management system should be able to coordinate the switching of the capacitor banks to obtain an optimal switching scheme for the desired time horizon. An optimal capacitor switching scheme can help increase the efficiency of the system and reduce the need for maintenance and upgrades for distribution equipment and lines.

1.2 Objectives

The main objective of this dissertation is to develop novel methods to increase the performance and reliability of the utility electrical system at the distribution feeder level. More specifically, this dissertation has developed algorithms to resolve the voltage profile monitoring problem by accurately estimating the voltage profile of a radial distribution feeder using forecasted load demands and a limited number of monitoring points. The algorithms can be executed with the information from the monitoring equipment already typically installed at the substation and thus can minimize additional capital investment for the installation of monitoring equipment. Also, due to the small amount of monitoring information needed, the voltage profile estimation will not over burden the power system's communication network. As an additional benefit, the load demand forecasting offers more information for infrastructure decisions in utility planning and operation departments in various distribution management functions such as intelligent feeder reconfiguration. The voltage profile estimation can also benefit utility operating departments and can be used in distribution system analysis.

Another objective of this dissertation is to use the results of the load and voltage profile estimations to develop an algorithm to perform optimal capacitor bank switching for the available capacitor banks on distribution feeders. The dissertation has integrated the voltage profile estimation and capacitor bank switching algorithms to create an intelligent centralized monitoring and control scheme for a radial distribution feeder. The day-ahead and hour-ahead forecasted load and voltage conditions allow the formation of a comprehensive and coordinated strategy of controlling reactive power compensation resources. Switching transactions can be reduced by using the algorithm to plan a day-ahead schedule of the capacitor operations with desired switching objective functions.

To achieve the dissertation objectives, the dissertation is organized into three main tasks. The division of work, allowed the software to be modular and individual tasks can be easily upgraded when required. The first task designed short-term load forecasting software to perform load profile and customer load demand forecasting for distribution feeders. The second task developed a voltage profile estimation algorithm for a distribution feeder with only a limited number of voltage monitoring points. The third task constructed a proactive optimal capacitor bank switching algorithm for a feeder with a mixture of residential, commercial, and industrial loads. The preceding tasks are developed in greater detail in Chapter 3.

1.3 Contributions

This dissertation offers several contributions to the field of power systems. First, the dissertation offers an innovative perspective on distribution system analysis. Whereas most distribution systems are designed to react quickly to problems and disregard upcoming challenges that are outside its decision time, this dissertation has adopted an extended time decision period. Instead of reacting every moment in time and at times allowing the system to overcompensate, the system can adopt an extended time range approach and receive more input into the decision making process to create a more comprehensive solution. The proactive approach also permits the distribution management system to have more decision time to coordinate resources and allows more automation on the distribution system.

Second, the proposed algorithms offer a better prediction of localized customer energy demand at the distribution level through the use of an artificial neural network. Deployment of artificial neural network software on distribution systems is a relatively new application of the technology. The dissertation solves the challenge of computing a short-term load forecast with limited historical information on the distribution feeder.

The local load forecasts can also be utilize in other distribution system functions such as load shedding, load growth studies, feeder upgrade studies, and distributed generation.

Third, the dissertation offers an improved approach for the calculation of the voltage profiles of the distribution system. The voltage profile estimation method gives an overall view of the voltage conditions along the entire feeder instead of only at the substation bus for the feeder. It also requires a minimal amount of monitoring equipment to be deployed which can in turn reduce the capital investment for the monitoring equipment's installation, operation, and maintenance. The voltage profile estimation method is also useful in many other applications for the distribution system. For example, it can be utilized in areas such as stability analysis, voltage regulation, reactive power management, optimal capacitor placement, distributed generation placement, and optimal feeder reconfiguration.

Finally, while capacitor control is not a new function to distribution systems, using the combination of neural network software and power flow software to set and update the capacitor switching policy has not been presented in the existing literature. By focusing on extended time periods that are ignored by local controllers, this new approach allows an optimal switching strategy to be determined before overcompensating switching occurs. Using an extended time approach, an optimal solution for an entire day or week that minimizes the number of switching can be achieved to reduce maintenance costs. In addition, the dissertation introduces a sensitivity method to expedite the calculation of the acceptable switching sequences.

1.4 Contents of Dissertation

The contents of this dissertation are organized in four chapters. A brief description of each chapter is presented in this section.

Chapter 1 introduces the background and motivation of the dissertation. Also, the objectives of the research and the contributions of the dissertation to the research community are given.

Chapters 2 through 4 present the theory and application of the objectives developed for the dissertation. The first objective was to develop an algorithm to perform load profile and customer load demand forecasting for a radial distribution feeder. To accomplish this goal, a supervised learning Artificial Neural Network (ANN) was built to perform hour-ahead and day-ahead demand forecasting. The load forecasting design considerations and program implementation are presented in Chapter 2. Chapter 3 details the second objective of the dissertation which was to combine the load forecasts from the first objective with a three-phase power flow program to produce a voltage profile estimation algorithm for a radial distribution feeder.

Finally, the third objective used the load forecasts and voltage profile estimations to design optimal capacitor switching schemes for several objective functions. Chapter 4 presents the algorithms designed to solve the distribution capacitor bank switching. A sensitivity method for the capacitor switching algorithm is also included.

The results of each part of the intelligent monitoring and control algorithms are presented in Chapter 5. A real-world distribution feeder is described and the algorithms are applied to demonstrate how the algorithms can benefit the feeder. Final conclusions and discussion of future research that could enhance this dissertation's work are included in Chapter 6. Appendix A contains an index of the abbreviations used in the dissertation.

CHAPTER 2

LOAD PROFILE AND CUSTOMER DEMAND FORECASTING

Chapter 2 describes the various issues associated with constructing a load profile and customer demand forecasting program for a radial distribution feeder. Topics in the chapter include the categories of load forecasting, time frame choices, the various load forecasting techniques, and load forecasting design considerations. The software program structure and implementation are also presented in the chapter.

2.1 Load Profile and Customer Demand Forecasting

Customer load demand data is necessary to accurately study the behavior of electric distribution systems. Since the beginning of the electric power industry, load forecasting has been an important task in the planning and operation of the power system. The subject of load forecasting is a broad topic that encompasses many different types of techniques and objectives. This section will consider some of the requirements for a suitable distribution load forecasting software program for an intelligent monitoring and control system.

2.1.1 Categories of Load Forecasting

Load forecasting can be classified by the objective of the prediction. Two categories of forecasting are spatial load forecasting and operational load forecasting.

Spatial load forecasting is defined as the prediction of future electric demand by location and is mainly used by distribution planning departments to appropriate funds towards expansion of a power system. Spatial load forecasting is concerned with the location, magnitude, and the temporal characteristics [1]. In spatial load forecasting it is important to find both the long-term size of the system load and the location of new load.

Operational load forecasting is mainly concerned with the daily operations of the distribution system. It rarely considers load growth as one of its priorities. More interest is shown toward the magnitude prediction of established load buses. System stability, real-time and near-real-time operation, and system automation are some of the functions better served by an operational load forecasting program.

Since this dissertation is a study of short-range monitoring and control variables and because long-term load growth was not considered in the dissertation objectives, an operational approach was chosen due to its better correspondence with the monitoring and control objectives.

2.1.2 Load Forecasting Time Range

Load forecasts can also be classified into four categories by their time duration [2], [3]. The time categories are long-term load forecasting, medium-term load forecasting, short-term load forecasting, and very-short-term load forecasting.

Long-term load forecasts are computed from several months to over 10 years ahead. Medium-term load forecasts can be calculated from a few weeks to a few months. Long-term and medium-term load forecasts are associated with system planning operations such as system upgrades, fuel requirements, and managing regional system load consumption and growth.

Short-term load forecasts have time durations from an hour ahead to a few days ahead. Very-short-term load forecasts are load forecasts close to real-time operation that extend from one to a few minutes ahead of the forecast time [2]. Short-term load forecasts are concerned with the daily operation of the power system in such applications as unit commitment and contingency analysis. Very-short-term load forecasting can be useful in applications such as energy pricing and fault analysis.

Out of the four categories, this dissertation has focused on calculating short-term load forecasts for a radial distribution feeder. The short-term time duration is the most useful for intelligent monitoring and control functions such as optimal scheduling of reactive resources on the feeder.

2.1.3 Load Forecasting Techniques

There are different techniques to perform a short-term load forecast. Traditionally, load demand has been forecasted by several mathematical techniques, including regression analysis, time series analysis, general exponential smoothing, state space methods, and expert systems [4]. New methods such as statistical learning algorithms, fuzzy logic, and artificial neural networks have also been developed for short-term load forecasting. The features of some of the most common load forecasting technique are described in the following sections.

2.1.3.1 Regression Approach

In general, regression approaches are statistical methods that compute the relationship between a dependent variable and a set of independent variables. Many different types of regression have been applied to load forecasting. Multiple linear regression [4] and non-parametric regression [5] are two types of regression models that have been applied to load forecasting.

The multiple linear regression approach is formulated based on a functional relationship between the energy consumption and variables such as weather, customer classification, and time of day. The multiple linear regression equation is shown in Equation (2.1) [4], [6].

$$y(t) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \cdot x_i(t) + a(t) \tag{2.1}$$

where $y(t)$ is the electric load,

α_0 and α_i are regression coefficients,

$x_i(t)$ are the independent variables correlated with $y(t)$,

and $a(t)$ is a white noise variable.

The independent variables of the regression model are selected based on load studies or the experiences of the utility staff. Due to the strong correlation between load and weather, most regression models include weather temperature as an independent variable. The method of least squares is typically used to calculate the regression coefficients.

One deficiency in the multiple linear regression approach is that identifying the correct model to represent the relationships between input and output variables is a complex and protracted process. In addition, if there are unexpected variations in the input values then high forecasting errors can occur.

A further deficiency of the multiple linear regression approach is that the traditional regression approaches model the relationship between weather variables and load demands as a linear or piecewise-linear representation. However, the relationship between the load forecast and weather variables such as temperature does not always correlate in a linear manner. As a consequence, the traditional regression approaches do not have the adaptability to handle the non-linear temperature variation.

Another regression method used for load forecasting is called non-parametric regression. The benefit of non-parametric load forecasting is that the load model can be calculated from the input data instead of having to identify the model before the computation.

In non-parametric regression load forecasting, the electric load is expressed in terms of a multivariate Probability Density Function (PDF) of load and load affecting variables [5]. An estimate of the PDF can be found using non-parametric density estimation on the historical load data. The load forecast is calculated from a conditional expectation of the load using the PDF estimate. One variation of the non-parametric load forecast using product kernel estimators is shown in Equation (2.2) [5].

$$\hat{P}(x) = \frac{\sum_{i=1}^{n} \left\{ P_i \prod_{j=1}^{r} K\left(\frac{x_j - x_{ji}}{h_j} \right) \right\}}{\sum_{i=1}^{n} \left\{ \prod_{j=1}^{r} K\left(\frac{x_j - x_{ji}}{h_j} \right) \right\}} \tag{2.2}$$

where $\hat{P}$ is the conditional expectation of the load,

$\mathbf{x}$ is a vector of load affecting variables,

P is an average hourly load,

n is the number of sets of $(P_i, \mathbf{x}_i)$ in the historical data,

K is a kernel,

and h is a smoothing parameter.

2.1.3.2 Similar-Day Approach

The similar-day approach searches past load data for days with similar time and climate characteristics as the forecast date. If similar time and climate characteristics are found in the historical data, then the matching day's load is selected as the predicted energy demand for the forecast day [7]. The similar-day approach suffers from poor adaptability to changing load conditions.

2.1.3.3 Time Series Approach

Time series analysis has been used in many areas including economics, physics geology, and digital signal processing. The time series approach has also been one of the main methods of load forecasting used in the electric power industry and several different time series methods have been developed over the years. Some examples of the time series methods are Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Autoregressive Moving Average with Exogenous Variables (ARMAX), and Autoregressive Integrated Moving Average with

Exogenous Variables (ARIMAX) [7]. An introduction to the equations involved in the common time series approaches is briefly presented.

In the ARMA method, an Autoregressive (AR) process and a Moving-Average (MA) process are combined. If the present value of the time series is $y(t)$, then it can be composed in terms of its previous values and with the present and previous values of a white noise series to form the ARMA model. Equation (2.3) shows the ARMA model with p autoregressive terms and q moving average terms.

$$y(t) = e(t) + \sum_{i=1}^{p} \varphi_i \cdot y(t-i) + \sum_{i=1}^{q} \theta_i \cdot e(t-i) \tag{2.3}$$

where $y(t)$ is the electric load,

φ_i are the AR parameters of the model,

θ_i are the MA parameters of the model,

and $e(t)$ is a white noise variable.

The ARMA method in Equation (2.3) is often specified in terms of a backshift operator, also known as a lag operator. The backshift operator is multiplied by a present time element to produce a previous time element as illustrated in Equation (2.4).

$$B \cdot y(t) = y(t-1) \tag{2.4}$$

where B is the backshift operator,

and $y(t)$ is the electric load.

For time element m, the backshift operator can be expressed by Equation (2.5).

$$B^m \cdot y(t) = y(t - m) \tag{2.5}$$

Equation (2.6) shows the ARMA method in terms of the backshift operator and with p autoregressive terms and q moving average terms.

$$\left(1 - \sum_{i=1}^{p} \varphi_i \cdot B^i\right) y(t) = \left(1 + \sum_{i=1}^{q} \theta_i \cdot B^i\right) e(t) \tag{2.6}$$

where φ_i are the AR parameters of the model,

B^i are the backshift operators,

$y(t)$ is the electric load,

θ_i are the MA parameters of the model,

and $e(t)$ is a white noise variable.

The ARIMA method is obtained by integrating the ARMA method. The ARIMA method considers both the autoregressive and moving average processes in addition to integrating with difference variables. Using the backshift operator, the ARIMA model is more easily determined. Equation (2.7) illustrates the ARIMA method in terms of the backshift operator.

$$\left(1-\sum_{i=1}^{p}\varphi_i \cdot B^i\right)(1-B)^d\, y(t) = \left(1+\sum_{i=1}^{q}\theta_i \cdot B^i\right)e(t) \tag{2.7}$$

where φ_i are the AR parameters of the model,

B^i are the backshift operators,

d is a positive integer,

$y(t)$ is the electric load,

θ_i are the MA parameters of the model,

and $e(t)$ is a white noise variable.

Equation (2.8) shows the ARMAX model with p autoregressive terms, q moving average terms, and b exogenous input terms.

$$y(t) = e(t) + \sum_{i=1}^{p}\varphi_i \cdot y(t-i) + \sum_{i=1}^{q}\theta_i \cdot e(t-i) + \sum_{i=1}^{b}\eta_i \cdot d(t-i) \tag{2.8}$$

where $y(t)$ is the electric load,

φ_i are the AR parameters of the model,

θ_i are the MA parameters of the model,

$e(t)$ is a white noise variable,

η_i are parameters of the exogenous inputs,

and $d(t)$ is a external time variable.

Equation (2.9) displays the ARMAX method in terms of the backshift operator with p autoregressive terms, q moving average terms, and b exogenous input terms.

$$\left(1-\sum_{i=1}^{p}\varphi_i \cdot B^i\right)y(t)=\left(1+\sum_{i=1}^{q}\theta_i \cdot B^i\right)e(t)+\left(\sum_{i=1}^{b}\eta_i \cdot B^i\right)d(t) \tag{2.9}$$

where φ_i are the AR parameters of the model,

B^i are the backshift operators,

d is a positive integer,

$y(t)$ is the electric load,

θ_i are the MA parameters of the model,

and $e(t)$ is a white noise variable.

The ARIMAX method is obtained by integrating the ARMAX method. Equation (2.10) shows the ARIMAX method in terms of the backshift operator with p autoregressive terms, q moving average terms, and b exogenous input terms.

$$\left(1-\sum_{i=1}^{p}\varphi_i\cdot B^i\right)(1-B)^d\,y(t)=\left(1+\sum_{i=1}^{q}\theta_i\cdot B^i\right)e(t)+\left(\sum_{i=1}^{b}\eta_i\cdot B^i\right)d(t) \tag{2.10}$$

where φ_i are the AR parameters of the model,

B^i are the backshift operators,

d is a positive integer,

$y(t)$ is the electric load,

θ_i are the MA parameters of the model,

and $e(t)$ is a white noise variable.

One weakness of the time series approach is that weather is not considered in the forecasting model. Weather is an important factor to load forecasting models since there is a strong correlation between power consumption and weather variables such as temperature [8], [9]. Another weakness is that the time series approach suffers from insufficient adaptability. The time series approach can perform well under normal conditions, but unexpected changes in the environment can appreciably degrade the performance of the forecast.

2.1.3.4 General Exponential Smoothing Approach

General exponential smoothing is the application of discounted least squares to the fitting of certain functions to time series data [10]. Exponential smoothing has the ability to assign more weight to recent observations and exponentially less weight to older observations. In the general exponential smoothing approach, the forecasted load y(t) is modeled as a linear combination of the known load and a white noise component as shown in Equation (2.11) [4], [11].

$$y(t) = \beta(t)^T f(t) + \varepsilon(t) \tag{2.11}$$

where $y(t)$ is the load at time t,

$\beta(t)$ is the coefficient vector,

$f(t)$ is the fitting function vector for the system,

and $\varepsilon(t)$ is a white noise vector.

The coefficients, in the coefficient vector $\beta(t)$, are required to slowly change. If the change in the coefficients is gradual over a time span greater than or equal to the maximum lead time, then the coefficients can be considered constant. The load forecasts can then be found by extrapolating Equation (2.11) using a fitting function and estimates of the coefficients [4].

Similar to the time series methods, a weakness of the general exponential smoothing approach is that it does not incorporate weather conditions into the forecasting model. Future implementations of the general exponential smoothing approach should incorporate weather variables into the forecasting model in order to increase the forecast accuracy.

2.1.3.5 State Space Approach

In the state space approach, the forecasted load is modeled as a state variable using state space formulation and a Kalman filter. Two sets of equations govern the process; the system state equations and the measurement equations. The system state space equations are shown in Equation (2.12) and the measurement equations are shown in Equation (2.13) [4], [12].

$$\mathbf{x}_{k+1} = \mathbf{F}_{k+1,k}\mathbf{x}_k + \mathbf{w}_k \tag{2.12}$$

$$\mathbf{y}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k \tag{2.13}$$

where $\mathbf{x}_k$ is the system state vector at time k,

$\mathbf{F}_{k+1,k}$ is the state transition matrix taking the state $\mathbf{x}_k$ from time k to k+1,

$\mathbf{w}_k$ is an independent, zero-mean, Gaussian noise vector with a known covariance matrix $\mathbf{Q}_k$,

$\mathbf{y}_k$ is the load measurement vector at time k,

$\mathbf{H}_k$ is a time-varying observation matrix which maps the true state space into the observed space,

and $\mathbf{v}_k$ is an independent, zero-mean, Gaussian noise vector with a known covariance matrix $\mathbf{R}_k$.

The Kalman filter has two stages of computation which are often called predict and update. If there is no observed data then an initialization stage can be estimated using Equation (2.14) and Equation (2.15). The predict phase calculates a state estimate from the previous step to produce a new estimate of the state at the new step. The predict phase is expressed in Equation (2.16) and Equation (2.17). The update phase improves the estimate from the predict phase to obtain a more accurate state estimate. The update phase is written in equation form in Equation (2.18), Equation (2.19), and Equation (2.20) [12].

Initialization: If necessary, for k=0, set:

$$\hat{\mathbf{x}}_0 = \mathrm{E}[\mathbf{x}_0] \tag{2.14}$$

$$\mathbf{P}_0 = \mathrm{E}[(\mathbf{x}_0 - \mathrm{E}[\mathbf{x}_0])(\mathbf{x}_0 - \mathrm{E}[\mathbf{x}_0])^{\mathrm{T}}] \tag{2.15}$$

where $\hat{\mathbf{x}}_0$ is the initial estimate of the state,

$\mathbf{x}_0$ is the initial state,

$\mathrm{E}[\mathbf{x}_0]$ is the expected value of $\mathbf{x}_0$,

and $\mathbf{P}_0$ is the initial error covariance matrix.

Predict Stage: For k = 1, 2, …, compute:

State estimate propagation

$$\hat{\mathbf{x}}_{k}^{-} = \mathbf{F}_{k,k-1}\hat{\mathbf{x}}_{k-1}^{-} \tag{2.16}$$

Error covariance propagation

$$\mathbf{P}_{k}^{-} = \mathbf{F}_{k,k-1}\mathbf{P}_{k-1}\mathbf{F}_{k,k-1}^{T} + \mathbf{Q}_{k-1} \tag{2.17}$$

where $\hat{\mathbf{x}}_{k}^{-}$ is an a priori state estimate vector,

$\mathbf{F}_{k,k-1}$ is a transition matrix taking the state estimate $\hat{\mathbf{x}}_{k-1}^{-}$ from time k-1 to k,

$\hat{\mathbf{x}}_{k-1}^{-}$ is an a posteriori state estimate vector,

$\mathbf{P}_{k}^{-}$ is an a priori covariance matrix,

$\mathbf{P}_{k-1}$ is an a posteriori covariance matrix,

and $\mathbf{Q}_{k-1}$ is an a posteriori matrix of known covariance matrix $\mathbf{Q}_{k}$.

Update stage: For k = 1, 2, …, compute:

Kalman gain matrix

$$\mathbf{G}_{k} = \mathbf{P}_{k}^{-}\mathbf{H}_{k}^{T}[\mathbf{H}_{k}\mathbf{P}_{k}^{-}\mathbf{H}_{k}^{T} + \mathbf{R}_{k}]^{-1} \tag{2.18}$$

State estimate update

$$\hat{\mathbf{x}}_{k} = \hat{\mathbf{x}}_{k}^{-} + \mathbf{G}_{k}(\mathbf{y}_{k} - \mathbf{H}_{k}\hat{\mathbf{x}}_{k}^{-}) \tag{2.19}$$

Error covariance update

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{G}_k \mathbf{H}_k)\mathbf{P}_k^- \tag{2.20}$$

where $\mathbf{G}_k$ is the Kalman gain matrix,

$\mathbf{P}_k^-$ is an a priori error covariance matrix

$\mathbf{H}_k$ is a time-varying observation matrix,

$\mathbf{R}_k$ is a known covariance matrix,

$\hat{\mathbf{x}}_k$ is an state estimate vector,

$\hat{\mathbf{x}}_k^-$ is an a priori estimate vector,

$\mathbf{y}_k$ is the load measurement vector at time k,

and $\mathbf{P}_k$ is the error covariance matrix.

In load forecasting, the predict stage is executed where the state estimate propagation and error covariance propagation are determined. The update stage is then executed where the Kalman gain matrix is calculated and then the state estimate vector and error covariance matrix are updated to improve their accuracy. The process is then repeated for each additional time step.

The identification of the system model and parameters is difficult in the state space approach for load forecasting. For example, the estimates for the white noise covariance matrices $\mathbf{Q}_k$ and $\mathbf{R}_k$ are not easily obtained in this approach [4].

2.1.3.6 Expert Systems

Expert systems, also known as knowledge-based systems, were developed to apply the knowledge and reasoning of human experts to a specific task. Expert systems have been applied to various power system functions, including short-term load forecasting [13]-[16].

In the area of short-term load forecasting, the hourly load is calculated using a knowledge base of time, economic, and weather data and a set of rules. A reference day is selected which is then altered with additional rules to account for load and weather variations in the forecasted day.

Expert systems are beneficial for tasks that have repetitive decisions since expert systems have an ordered decision model that never forgets steps and can store significant amounts of decision making information. However, there are several disadvantages of expert systems. First, expert systems must have included all rule based knowledge for the forecast problem since they cannot create new responses for atypical events. There is a lack of adaptability in expert systems, since adjusting the rules requires a modification of the knowledge base when there are changes in the environment. In addition, decision making steps are not always clear and if there are errors in the knowledge base then the output accuracy can be reduced. With these disadvantages, expert systems were not considered an appropriate choice of short-term load forecasting for the distribution feeder.

2.1.3.7 Artificial Neural Network Load Forecasting

Another method of predicting load demand is to use an artificial neural network (ANN) as a short-term load forecasting program. In general, ANNs are mathematical models originally based on the theoretical operation of the human brain. An ANN forms a parallel connection between parameter elements and processing elements called neurons. The function of the ANN is established by the connection weights, the neuron processing unit, and the network configuration.

ANNs have been applied in areas such as pattern classification, function approximation, regression analysis, and data filtering. ANNs have been used in the power industry for various functions such as fault classification, fault diagnosis, system protection, unit commitment, and economic dispatch [17]-[23].

One of the most important aspects of ANNs is their ability to learn from their environment. An ANN can learn complex relationships between input data and output data through the adjustment of connection weights. For example, it has been observed that load forecasts are sensitive to changes in the weather [24]. Mapping the relationship between the forecasted load and the weather conditions can be complex process. However, ANNs can effectively discern the relationship internally and can determine how much weight to give the weather conditions on different types of days. The ability of ANNs to determine the variable relationships from historical data without selecting an appropriate model is a significant advantage over traditional load forecasting techniques.

ANNs have several additional advantages over traditional methods of load forecasting. One advantage is that ANNs can quickly solve large scale problems through the ANN's parallel distributed structure that traditional methods cannot manage. ANNs can also utilize nonlinear elements that create nonlinear computations in the neural network. The support of nonlinearity in the network permits the ANN to perform nonlinear tasks such as load forecasting with more accuracy than through linear methods. Another advantage is that ANNs have the ability to adapt to new changes in the neural network's environment. ANNs can be retrained with new training data as more data becomes available to the neural network [25].

2.1.4 Selected Load Forecasting Technique

Most load forecasting methods produce acceptable results, however, ANNs have the ability to increase the accuracy of the short-term load forecasts and deliver improve reliability of the forecasted values. ANNs provide the best method for estimating a short-term operational load forecast on the distribution feeder due to the ANN's inherent ability to learn complex nonlinear relationships. While there are some challenges for implementing an ANN in a distribution system environment, the challenges are not insurmountable and the ANN can still be successfully applied for a radial distribution feeder. Consequently, the artificial neural network load forecasting technique was selected for the load customer demand forecasting in this dissertation.

2.2 Artificial Neural Network for Customer Demand Forecasting

The following sections describe the design considerations and implementation of an ANN to forecast the load of a radial distribution feeder.

There is no standard ANN Short Term Load Forecaster (ANNSTLF) that can be applied to every distribution feeder. The fundamental structure and algorithms of the ANNSTLF can be designed in advance but the parameters must be customized for each implementation. Some elements such as the number of hidden neurons and the selection of activation functions are dependent on the system and available data. Since the intelligent monitoring and control software was designed to be modular, when changes to other techniques are required or advances to ANNSTLF technology become available the modifications can be easily substituted into the program.

The procedure to design an ANNSTLF involves selecting the input variables, selecting the network structure, and for some types of ANNSTLFs preparing the network with an offline training procedure. The following ANNSTLF was implemented for a distribution feeder from a utility company and the analysis is based on its performance. The results are presented in Chapter 5.

2.2.1 Selection of Input Variables

The ANNSTLF input variables are selected from load affecting factors that have significant impact on the system load variation. Presently, the selection of input variables in most ANNSTLFs is done through heuristic experimentation where decisions are based on experience and knowledge of the system. The most widely considered variables in short-term load forecasting can be classified into three groups: time, load, and weather [26]. Time variables consist of variables such as the hour and day of the forecast. Load variables are the past energy consumption on the feeder.

Weather variables are variables representing the weather conditions near the feeder such as temperature, humidity, wind speed, and wind direction.

The input variables that were chosen for the distribution system ANNSTLF in the dissertation were the hour of the load forecast, three previous total load values at the substation, and the forecasted temperature for the hour of the load forecast. The hour of the forecast (h) is set to a bounded range as represented in Equation (2.21) [2]. The output of the ANN is the total load forecast for the distribution feeder.

$$H = \cos\left(\frac{2\pi \cdot h}{24}\right) \tag{2.21}$$

where h is the hour of the forecast.

2.2.2 Standardization of Data

The training data and input data should be standardized before it is used in the network. Standardizing the data means that the input and output data is rescaled to a different range, often performed by subtracting a measure of location and dividing by a measure of scale. Standardization of the input data is important because the range of the values can disrupt the error correcting process. If the input variables are on different ranges, then the larger input values will have a more prominent contribution to the output error. As a consequence, the error correction algorithm will focus on correcting the larger ranged variables and neglect the information from the smaller ranged variables. Standardizing the input variables can also help avoid weight saturation. Data standardization can reduce the estimation errors and calculation time of the ANN [27].

Equation (2.22) demonstrates the procedure to scale the input data [2].

$$s = \frac{x - \overline{x}}{\sigma_x} \tag{2.22}$$

where s is the scaled input data,

x is the input data,

$\overline{x}$ is the mean of the input data x, $\overline{x} = \frac{\sum_{i=1}^{n} x_i}{n}$,

n is the number of data samples,

and σ_x is the standard deviation of the input data x, $\sigma_x = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n}}$.

After the ANNSTLF has successfully calculated the forecast value, the output data must be converted back to the original data range. Equation (2.23) shows the procedure to perform the inverse standardization on the output data [2].

$$x = \overline{x} + (\sigma_x \cdot s) \tag{2.23}$$

where x is the output data,

$\bar{x}$ is the mean of the input data x, $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$,

n is the number of data samples,

σ_x is the standard deviation of the input data x, $\sigma_x = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n}}$,

and s is the scaled output data.

2.2.3 ANNSTLF Architecture

The choice of network architecture for the ANNSTLF is an important issue in the design of the neural network since the ANN structure affects the selection of the learning algorithm that trains the network. ANN structures consist of one or more layers of artificial neurons. Artificial neurons are processing units that normally contain a set of connection weights, summing junction, and an activation function. There are different ways of connecting the artificial neurons and many ANN architectures have been studied over the years. The three main categories of network structures are single-layer feedforward networks, multi-layer feedforward networks, and recurrent networks.

A single-layer feedforward network is a network model where an input layer of source nodes is connected forward to an output layer of neurons through a series of weights. Feedforward networks moves information in the direction from the input layer to the output layer. Feedforward networks have no feedback loops or lateral connections within the layers. Figure 2.1(a) illustrates a single-layer feedforward network.

Multi-layer feedforward networks are ANNs that have an input layer of sources nodes, and output layer of neurons, and one or more hidden layers of neurons commonly called hidden neurons. A common ANN in this category is the Multi-layer Perceptron (MLP) network which has been used in several load forecasting software programs [24], [28]-[31]. Figure 2.1(b) illustrates a multi-layer feedforward network.

Recurrent networks are ANNs that have one or more feedback loops. Recurrent networks can be single or multi-layered with one or more hidden layers. The feedback loops can be connected either from layer to layer or a self-feedback manner. Self-feedback is when the neuron output is fed back into the input of the same neuron. A well known recurrent ANN is the Hopfield Network. Figure 2.1(c) illustrates a single-layer recurrent network with self-feedback loops.

Of the three fundamental ANN architectures, the most useful structure for load demand forecasting is multi-layer feedforward networks. The ANN designed for the intelligent monitoring and control software uses a multi-layer feedforward network with one hidden layer.

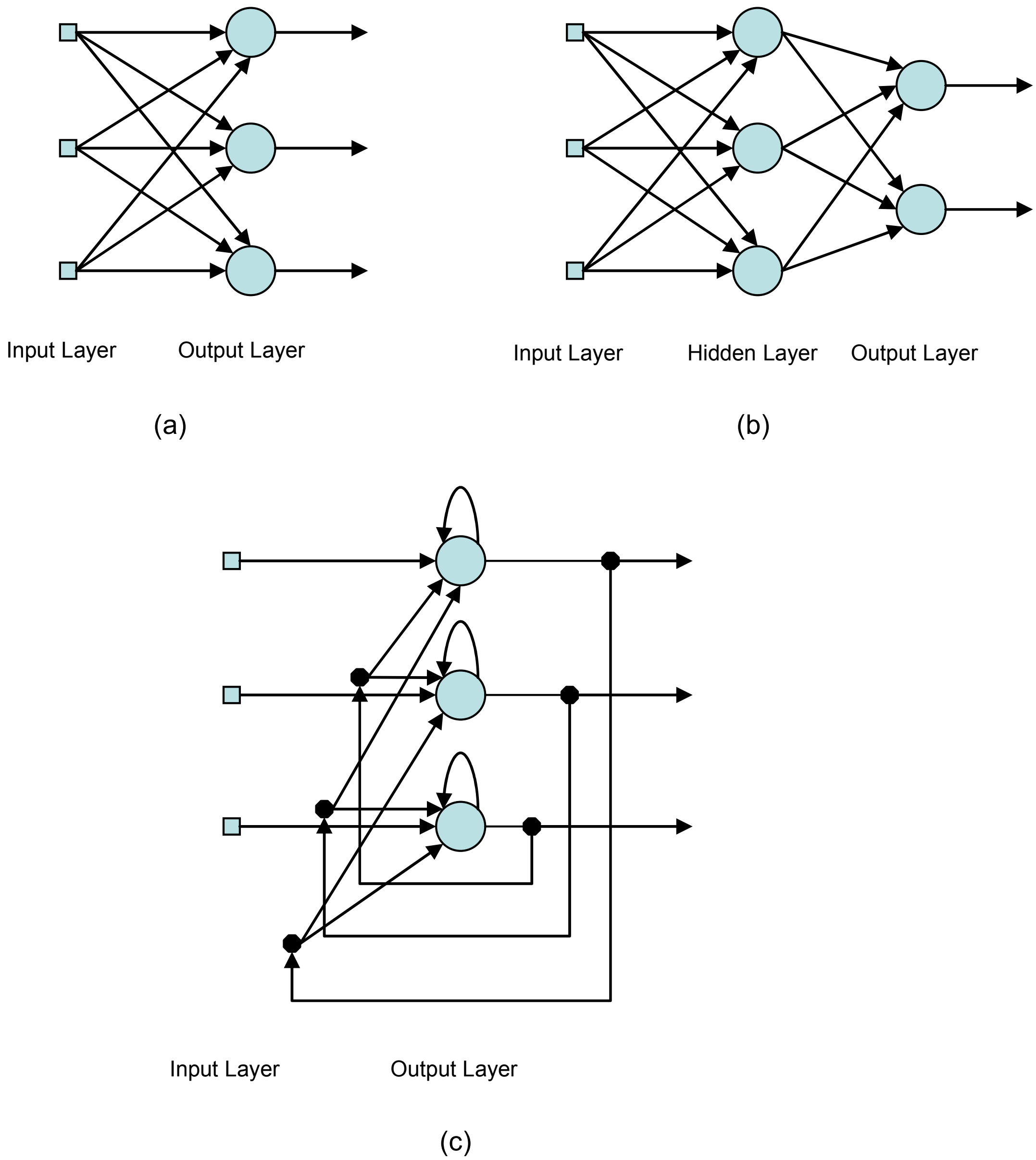

Figure 2.1: Artificial Neural Network Structures. (a) Single-Layer Feedforward Network. (b) Multi-Layer Feedforward Network. (c) Single-Layer Recurrent Network with Self-Feedback Loops.

2.2.4 Load Patterns

Different days of the week can produce different load patterns. Saturday and Sunday generally have different load patterns than days in the business week since many people do not work on the weekend which in turn reduces the commercial and industrial electricity demands. Similarly, the load patterns on Mondays and Fridays are different from other weekdays. Normally, at the beginning of the business week on Monday mornings, commercial and industrial businesses resume production and the resulting startup loads contribute to the difference in load patterns. On Fridays, commercial and industrial businesses may reduce production due to the proximity of the weekend. In addition, there are different load patterns for the different hours of each day.

To account for the daily load variations, the distribution system short-term load forecast software utilizes several neural networks for the different types of day and hour periods. In addition, a moving data window collection is employed to account for the variations in seasonal load data. These techniques allow the distribution system short-term load forecast software to train each network with a comparable range of values to increase the accuracy of the ANNs for the different load patterns.

For the distribution system short-term load forecast software, there are 20 different neural networks for one feeder. Table 2.1 displays the network type and the associated day and hours for each ANNSTLF. For example, the load forecast for Monday at 2 a.m. would have a network type of zero (0) while the load forecast for Friday at 10 p.m. would have a network type of fourteen (14).

Additional customization of the MLP ANNSTLF requires that the number of hidden neurons be selected for each network type. The number of hidden neurons is important because if there are too few neurons then there will not be enough computational capacity to learn the complex relationships of the data. If there are too many neurons, the ANN will memorize the data instead of learning the complex relationships. The number of hidden units depends on the distribution feeder and network type of the ANN and is experimentally chosen for each ANN network type.

Table 2.1: Day Range and Hour Range for each Artificial Neural Network Type

Network Type	Day Range	Hour Range
0	Monday	1 a.m. - 5 a.m.
1	Monday	6 a.m. - 8 a.m.
2	Monday	9 a.m. - 4 p.m.
3	Monday	5 p.m. - 9 p.m.
4	Monday	10 p.m. - Midnight
5	Tuesday - Thursday	1 a.m. - 5 a.m.
6	Tuesday - Thursday	6 a.m. - 8 a.m.
7	Tuesday - Thursday	9 a.m. - 4 p.m.
8	Tuesday - Thursday	5 p.m. - 9 p.m.
9	Tuesday - Thursday	10 p.m. - Midnight
10	Friday	1 a.m. - 5 a.m.
11	Friday	6 a.m. - 8 a.m.
12	Friday	9 a.m. - 4 p.m.
13	Friday	5 p.m. - 9 p.m.
14	Friday	10 p.m. - Midnight
15	Saturday - Sunday	1 a.m. - 5 a.m.
16	Saturday - Sunday	6 a.m. - 8 a.m.
17	Saturday - Sunday	9 a.m. - 4 p.m.
18	Saturday - Sunday	5 p.m. - 9 p.m.
19	Saturday - Sunday	10 p.m. - Midnight

Another important design decision is the choice of activation functions at each layer's neurons. Activation functions introduce nonlinearity into the ANN. There are several types of activation functions used in ANNs including the Heaviside step, piecewise linear, and sigmoid functions such as the hyperbolic tangent. A popular choice for an activation function for the MLP ANNSTLF is the hyperbolic tangent due to the ease of computing its first derivative for the back-propagation weight correction process [32].

2.2.5 Learning Algorithm and Training Process

An important feature of ANNs is the ability to learn complex input and output mappings. Within the subject of ANNs there are three fundamental learning models which are called learning with a teacher, learning with a critic, and learning without a teacher.

In the learning with a teacher model, also called supervised learning, the system is stimulated with a set of input-output examples in order to modify the weights within the network. A set of inputs is presented to the input layer and an output is calculated by the ANN. The output response due to the input set is compared to the desired output response and the network weights are adjusted to minimize the difference between the desired output and actual output response. The training process is repeated until the network weights are stabilized. Most training for supervised learning ANNs occurs as an offline process where the network is trained before being employed.

One problem with supervised learning is that it requires complete historical data in order to train the network. Incomplete and missing data must be corrected prior to training the ANN.

Learning without a teacher, also known as unsupervised learning is a self organizing learning algorithm where patterns are found in the input data without a set of input and output examples. Some unsupervised learning algorithms use a competitive learning rule where the artificial neurons located in a competition layer compete for a chance to control the neural network based on the input data. Both online and offline implementations exist for unsupervised learning ANNs. Statistical modeling, compression, and data clustering are some of the areas that use ANNs with unsupervised learning.

Learning with a critic, usually referred to as reinforcement learning, is an online process where the network learns by interacting with the system to map data to actions in order to maximize a numerical reward signal. Reinforcement learning does not present a set of input-output examples to the network to adjust the network weights but instead tries to discover which actions yield the most reward. Reinforcement learning is often considered a type of learning without a teacher in some neural network texts [25].

A problem with utilizing reinforcement learning for load forecasting is that in order to reward the preferred values the reinforcement learning ANN must explore new values it has not selected before. The ANN must gradually exploit the values that appear to give the maximum reward with the present knowledge while also exploring many new values to increase knowledge of the system data. Since it is not possible to both explore or exploit with any single data selection, the ANN must balance the need of maximizing the reward and improving the knowledge of the system data. This exploitation and exploration process which is not present in most implementations of supervised learning leads to a longer training period with the reinforcement learning algorithm.

In contrast, the supervised learning can be initially performed ahead of time in a batch offline process and then can be updated on a daily or hourly basis when new data is available using an incremental offline training procedure. This incremental update approach can significantly reduce the required training time of the ANN.

Both, reinforcement learning and unsupervised learning are attractive for applications where there is no available historical data. If however historical data is present, supervised learning can often perform faster and with a better accuracy at predicting future states. In addition, there have been many implementations of ANN load forecasters that use supervised learning as the learning paradigm. Consequently, due to the success of previous ANN implementations and the speed of training, this dissertation will focus on a supervised learning approach called back-propagation.

2.2.5.1 Back-Propagation Algorithm

The back-propagation algorithm is a popular and computationally efficient supervised learning algorithm for MLP ANNs which is based on error correction learning [25]. During training a forward pass and backward pass are applied to the ANN with each example data set. The forward pass is presented at the input layer and is transmitted forward through the network of weighted connections and neurons until the output layer is computed.

After the forward pass, the computed output is compared to desired output by computing the squared error between each output. The backward pass is then performed where the network weights are tuned by transmitting the error back through the ANN. The standard back-propagation algorithm uses a gradient descent optimization when adjusting the weights. Also in the back-propagation algorithm, a parameter called the learning rate can be modified to raise or lower the speed of learning by adjusting the size of the weight changes. Due to the gradient descent algorithm, for the standard back-propagation learning, the activation functions at each neuron must be differentiable. A detailed derivation of the back-propagation algorithm can be found in the ANN literature [25], [33], [34].

2.2.5.2 Training and Validation of ANN

At the beginning of the training process, the weights are initialized with random numbers or by recalling the previously trained weights. If no training has previously occurred then a batch training process must be executed in which several months or years of data must be presented to the ANN. If training has previously taken place then an incremental process can recall the weights from storage and then update the weights with a small number of example patterns.

As previously stated, training the ANN involves presenting example inputs to the input layer and comparing the computed output to the example's desired output. Many examples are needed to train the network. A good estimate of the required amount of hourly data is more than two years. At least two years is required in order to allow the ANNSTLF to discover the relationships between the load and different monthly patterns and seasons. On batch training, the training is stopped when the squared error is less than a specified minimum error and validation goal or if the iteration is greater than the maximum number of iterations. For incremental training the training is performed for a specified number of iterations. Figure 2.2 displays a flowchart of the ANN's training procedure.

Problems can occur if the ANN is under-trained or over-trained. If the ANN is under-trained or over-trained then the weights may start to memorize the training data instead of learning the relationships between the output and inputs. In this undesirable issue, commonly called overfitting, the ANN operates well with data that has been observed with the training data but has poor performance with new data not in the training data set. To prevent overfitting, a validation data set is applied to the ANN instead of the training data set for several iterations to determine when to stop training. If the training error decreases while the validation error increases then the training procedure should be stopped at that iteration. Once the training of the ANN is completed and the network is validated, the neural network is ready to perform the load forecasting.

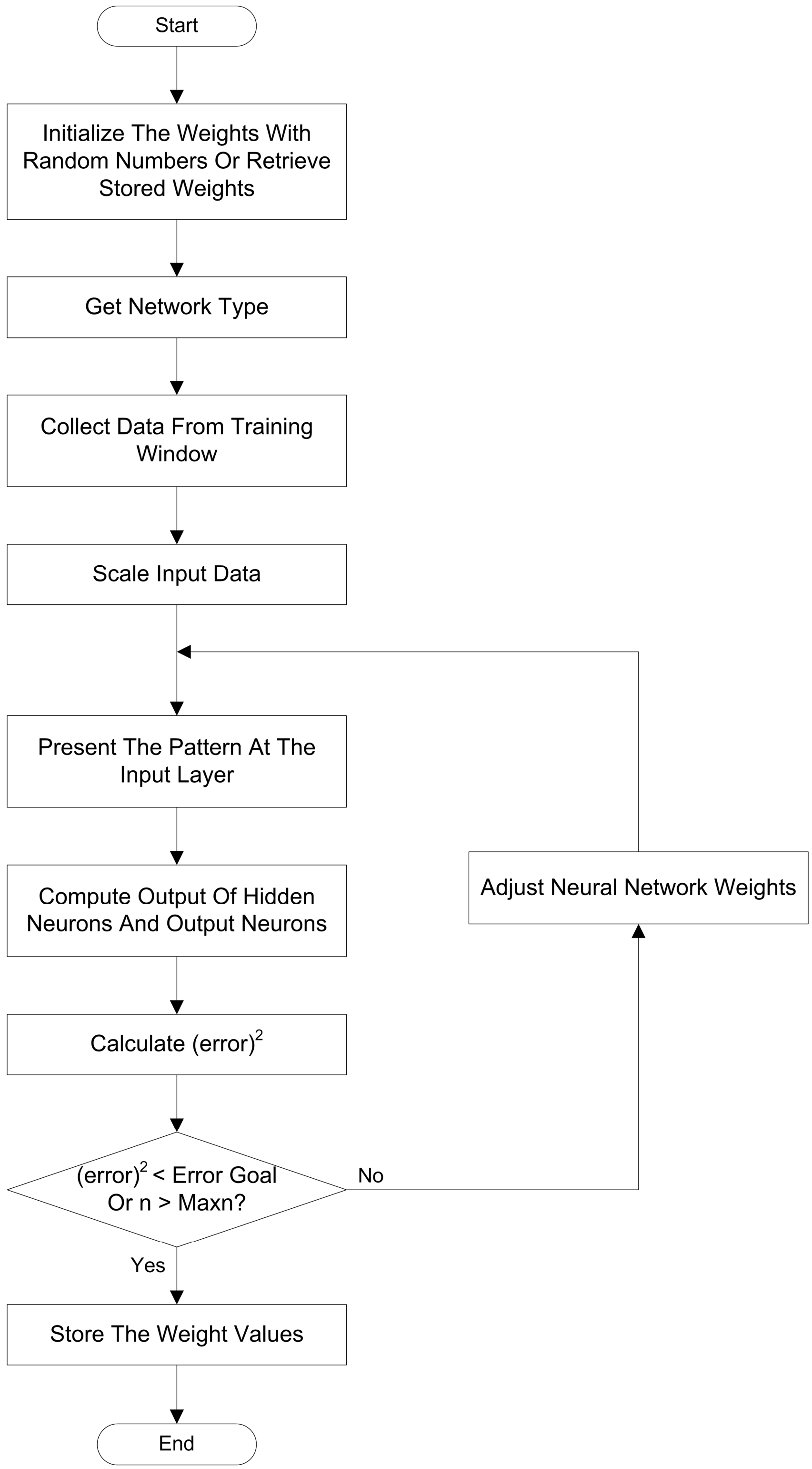

Figure 2.2: Flowchart of the Artificial Neural Network Training Procedure.

2.2.6 Implemented ANNSTLF Design

The implemented design of the distribution system ANNSTLF was a feedforward, supervised learning, multi-layer perceptron using back-propagation. The ANNSTLF has one hidden layer and one output, the forecasted load. This type of neural network has been successful in the past for predicting electric loads and provides a reasonable approximation of the feeder load [24], [28]-[31].

Figure 2.3 shows an overview of the artificial neural network design [2]. In Figure 2.3, L(d,h) is the output load forecast on day (d) and hour (h). For the inputs, H is the hour calculation of the load forecast found using Equation (2.21). L(d,h-1), L(d,h-2), and L(d,h-3) are the three previous load values at the feeder. Temp(d,h) is the forecasted temperature. Equations (2.24) and Equation (2.25) govern the ANN calculation process.

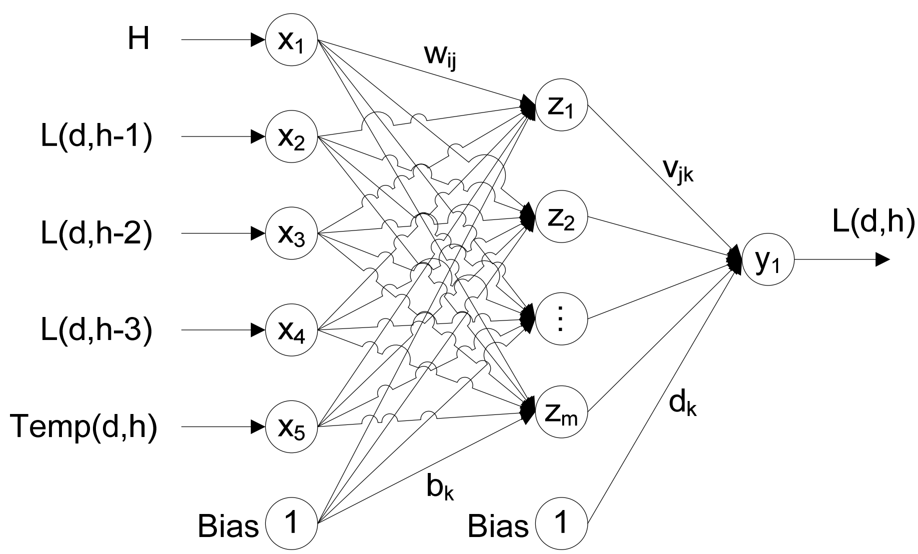

Figure 2.3: Overview of the Artificial Neural Network Design.

$$z_j = \varphi_h\left(\sum_{i=1}^{N} w_{ij} \cdot x_i + b_j\right) \tag{2.24}$$

where z_j is the output at the hidden neuron j,

φ_h is the activation function at the hidden layer,

N is the number of inputs,

w_{ij} are the input-hidden weights,

x_i is the input i,

and b_j are the input-hidden bias weights.

$$y_k = \varphi_o\left(\sum_{j=1}^{M} v_{jk} \cdot z_j + d_k\right) \tag{2.25}$$

where y_k is the output at the output neuron k,

φ_o is the activation function at the output layer,

M is the number of hidden neurons,

v_{jk} are the hidden-output weights,

z_j is the output at the hidden neuron j,

and d_k are the hidden-output bias weights.

For the Load Profile and Customer Demand Forecasting (LPCDF) software, the ANNSTLF utilizes a hyperbolic tangent activation function at the hidden layer and a linear activation function at the output layer.

2.2.7 Required Data

The dissertation's new method of forecasting load demand requires some information from the utility. First, customer classification for load buses on the feeder is needed. Each customer must belong to a customer class that characterizes its demand usage. Residential, residential multiple dwelling, commercial, and large industrial are examples of classification groups. In addition, customer demand survey data is required for the load allocation method. Customer demand survey data is data that is collected in order to determine customer classification categories and typical demand profiles for the customer class. It consists of representative samples of time of day demand data for a population of customers within a classification group. Customer demand survey data for each customer class is required.

Historical hourly temperature data is required for the training procedure and hourly forecasted data is required to run the ANNSTLF. Hourly temperature forecasted data can be downloaded from the internet at several weather forecasting sites. Also needed is the historical total energy demand in kilowatts at the substation for each hour of the day.

2.3 Load Profile Forecasting

An estimate of the load profile permits observation of the entire feeder load demand and an overview of each load's power requirements without installing any monitoring equipment at the individual load buses. Obtaining the load profile of a distribution feeder is important for various areas in power system analysis such as planning load growth, upgrading infrastructure, and load balancing.

2.3.1 Load Allocation of the Artificial Neural Network Forecast

One challenge with deploying an ANNSTLF to a distribution feeder is in the area of data collection. Since the ANNSTLF uses a supervised learning algorithm for the training procedure, the ANN must be trained to perform the load forecast in an offline process using historical data obtained from the utility. Unfortunately, most utilities normally do not collect and store historical hourly load data for each load bus on every distribution feeder. Collecting load data at each load bus would require the utility to install and maintain monitoring equipment at each load bus. Presently, installing monitoring equipment on every load bus is not economically feasible since the monitoring equipment would involve a substantial capital investment. Transmitting and storing large amounts of data through a power system's communications network would also require upgrades to the communication and data storage infrastructure. This means that training the ANN to forecast the load at each load bus is not practical. In order to find the predicted load profile of the feeder using an ANN another solution is needed.

One solution to the data collection challenge is to train the ANN to calculate the total load for the feeder at the substation and then allocate the total load to each load bus based on the load buses estimated percentage of the total. Most utilities do collect and store hourly load data at the distribution feeder circuit breaker in the substation. Figure 2.4 shows a simplified view of a radial feeder showing the known and unknown historical values.

As a result, this dissertation's method uses an ANN to estimate the total load of the feeder at the substation circuit breaker and then allocates a percentage of the total load to each load bus using an allocation procedure.

Therefore, each bus's load value must be estimated from the total load in order to find the feeder load profile. The percentage of the total load of each load bus is obtained from typical 24 hour customer classification load curves compiled from previous load studies conducted by the utility.

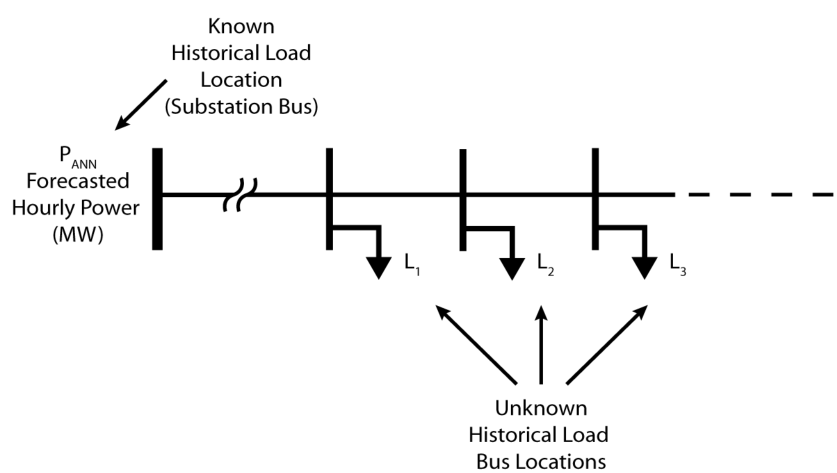

Figure 2.4: Known and Unknown Historical Values on the Feeder.

2.3.2 Load Profile Calculation

The 24 hour customer classification load curves are acquired from load studies where the utility performs a statistical analysis of the load characterization of each load bus for each hour of the day. To obtain the percentage of load at each bus, each load bus in the feeder would have a classified load curve based on its customer classification. For example, a load bus could be classified as a 24 hour commercial business and would have a load pattern for the day based on a typical case developed in the load study. At each hour of the day the load values from the classification curves are summed to obtain the total classification load. The classification load curve value at the desired bus is then divided by the total classification load to obtain the load percentage of the desired load bus. The load percentage is multiplied by the total forecasted load calculated by the ANNSTLF to obtain the estimated load at the desired bus. This procedure is presented in Equation (2.26) and Equation (2.27).

$$L\%_i(t) = \frac{\Gamma_i(t)}{\sum_{j=1}^{n} \Gamma_j(t)} \cdot 100 \tag{2.26}$$

where $L\%_i(t)$ is the percentage of load at bus i at time t,

$\Gamma_i(t)$ is the load classification value at bus i at time t,

and n is the number of load buses on the feeder.

$$LE_i(t) = \left(\frac{L\%_i(t)}{100} \right) \cdot P_{ANN}(t) \tag{2.27}$$

where $LE_i(t)$ is the load estimate at bus i at time t,

$L\%(t)$ is the percentage of load at bus i at time t,

and $P_{ANN}(t)$ is the total load forecast calculated by the ANN at time t.

2.3.3 Load Allocation Example

This section presents an example of how the load allocation procedure is accomplished using the load classification curves. Table 2.2 displays an abbreviated example of the classification curve data for a sample distribution feeder.

Table 2.2: Load Classification Curve Data for a Sample Distribution Feeder

Hour	1	2	3	4	5	6	…	24
	kW	kW	kW	kW	kW	kW	…	kW
Bus 1	5.14	6.21	2.71	6.31	3.63	5.44	…	8.69
Bus 2	1.19	0.42	0.03	1.40	0.04	1.33	…	2.22
Bus 3	16.71	15.44	13.10	9.73	10.09	10.27	…	17.89
Bus 4	18.95	14.92	13.14	14.65	12.50	11.99	…	22.98
Bus 5	15.23	13.03	9.94	9.47	9.82	10.96	…	17.99
Bus 6	20.86	15.79	13.65	16.53	16.01	14.22	…	21.93
Bus 7	18.39	14.93	10.70	14.20	10.99	12.76	…	18.96
Bus 8	5.33	5.26	2.45	2.73	3.80	3.65	…	5.17
Bus 9	10.58	7.60	6.84	6.23	5.12	7.20	…	11.28
Bus 10	6.44	6.37	5.86	5.37	5.59	2.95	…	8.65
Total	118.82	99.97	78.42	86.62	77.59	80.77	…	135.76

Equation (2.28) illustrates how to obtain the load percentage of bus 5 at hour 4 using Table 2.2.

$$L\%_5(4) = \frac{9.47}{86.62} \cdot 100 = 10.93\,\% \tag{2.28}$$

If the total load forecast from the ANNSTLF is calculated to be 88 kW at hour 4 then the forecasted load at bus is shown in Equation (2.29).

$$LE_5(4) = \frac{10.93\,\%}{100} \cdot 88\,\text{kW} = 0.1093 \cdot 88\,\text{kW} = 9.62\,\text{kW} \tag{2.29}$$

These calculations are performed on every load bus to obtain the hourly load profile of the feeder.

2.3.4 Future Improvements to the Load Allocation Algorithm

The load allocation algorithm uses customer load profile and meter data to estimate hourly percent load distribution along the feeder. This procedure can be improved where Advanced Meter Infrastructure (AMI) is implemented and communication technologies such as Broadband over Powerline (BPL), power line carrier (PLC), or other communication systems are available. BPL and PLC are communication technologies that transmit data over existing electric power lines to reduce the cost of installing new communication lines and infrastructure for power system communication.

For buses that have installed meters with communication functions, the load profile and customer demand forecasting program can treat the metered locations as known load and voltage values. Before the load allocation program is executed, it can acquire the load and voltage data from the meters. The load profile then can be calculated with better accuracy at the metered locations which will allow the load allocation program to improve the overall performance of the load profile estimate.

2.4 Chapter Conclusions

Knowledge of the load demand and load profile of a distribution feeder is important for designing intelligent monitoring and control systems for distribution power systems. Despite the obvious importance of load demand data for distribution system analysis and optimization, few reliable methods are available to forecast the load profiles of distribution feeders. There are several methods of forecasting the total load on a distribution feeder including regression, time series, and artificial neural networks but few have been developed to reliably calculate the load profile of the feeder.

Of the load forecasting methods available, the artificial neural network approach provides the best opportunity to forecast the distributed load along the feeder due to its inherent ability to perform nonlinear calculations, adapt to new changes in the input data, and incorporate weather data into the forecast. However, application of ANNs for load demand forecasting and load profile estimation at the distribution level of the power system has not been fully explored in the research literature. Consequently, this chapter presented a novel method of forecasting the customer load demand and feeder load profile for a radial distribution feeder using an artificial neural network and a load allocation algorithm.

Based on the design decisions described in this chapter, an artificial neural network software program was developed to forecast the total feeder load at the substation and a load algorithm function was created to find the load profile. In Chapter 5, the results of the load profile and customer demand forecasting program is presented for a sample distribution feeder. Chapter 3 employs the forecasted load profile data to develop a method of estimating the voltage profile for radial distribution feeders.

CHAPTER 3

VOLTAGE PROFILE ESTIMATION

This chapter discusses the subject of voltage estimation on distribution systems and introduces a novel voltage profile estimation method using the load profile forecast developed in Chapter 2. Topics in Chapter 3 include voltage estimation techniques for distribution systems, power flow techniques, and a description of the dissertation's voltage profile estimation.

3.1 Voltage Profile Estimation

In power systems, voltages must be maintained within the desired range with respect to their rated values to ensure the quality of the electric power supply. Information on the voltage conditions at each load location along a distribution feeder can be a valuable component in distribution system operation, planning, and analysis. With comprehensive knowledge of the feeder voltage conditions, the electric service quality, system reliability, and control of the distribution system can be improved.

Voltage issues can affect the quality of the electric supply and system reliability. When voltages shift beyond standard operating ranges, equipment can be tripped offline and cause significant economic expenses and customer frustration. More serious overvoltage and undervoltage problems can cause interruptions of the power supply. Voltage profile estimation can help predicting voltage conditions on the distribution lines and let control systems correct the voltage to acceptable levels.

Better control of distribution system resources can be accomplished with more effective monitoring strategies. For example, shunt capacitor banks must be switched online and offline based on the voltage conditions on the feeder. When the voltage is low on the feeder, the shunt capacitor banks are switched online to provide voltage support. Traditional switching schemes based upon local information may turn on multiple capacitor banks that can create excessive voltage rise and voltage transients. Better knowledge of the voltage profile can improve the coordination of the voltage regulation resources and reduce the overvoltage conditions associated with the capital resources.

Even though voltage monitoring of the feeder is beneficial for the overall reliability and control of the distribution system, utility capital constraints and communication infrastructure limits restrict the wide deployment and use of voltage monitoring equipment at the present time. In most cases, only a limited number of voltage monitoring equipment is available on the distribution lines. Consequently, this dissertation develops an algorithm to resolve the voltage profile monitoring problem by identifying the key locations for voltage measurement along the distribution system and estimating the voltage profile of the system through software simulation.

3.2 Voltage Estimation Techniques for Distribution Systems

A distribution system is a division of the power system where electricity is transferred from the high voltage transmission system to the end user. Distribution feeders are typically rated from 4.2 kV to 34.5 kV in the United States with 12.47 kV being the most common voltage rating [35]. Newer installations often use higher distribution voltages in the 25 kV voltage class.

3.2.1 Voltage Estimation on Distribution Systems

Distribution systems have different structures and operating conditions than transmission systems and thus require different voltage estimation methods. The unique design and service requirements of distribution systems must be taken into account to effectively estimate the voltage and power conditions.

Distribution systems are normally structured in radial, loop, or network configurations. Radial distribution systems are configured to transfer electricity through one path that travels from the substation to the electricity end user. The radial structure is the most common design and is the simplest to analyze since the power flows in one direction.

Loop distribution systems connect two paths between the substation and the electricity end user. Loop structures are more reliable than radial systems since there are two paths for the power to flow to the load. However, loop structures are more expensive to install compared to radial feeders as a result of the larger required conductors that must support the entire load on loop in case one end of the feeder is opened. Also, additional protection devices are required to protect loop feeders which have more complex protection schemes. In some cases, loop feeders have a normally open switch on the loop; however, this normal operation is actually a radial feeder with a backup supply path.

In distribution networks, the buses are connected together by multiple paths and the network is supplied by multiple connections to the substation. Distribution networks are often deployed using underground conductors in densely populated urban settings and are often more reliable than radial and loop systems since the flow of electricity can be redirected along other routes in cases of line contingencies. On the other hand, distribution networks are more expensive than radial and loop feeders because of the redundant infrastructure and the more complex protection schemes. Also, distribution networks are more difficult to analyze due to the many available paths through which the electric power can flow [35].

Since the radial structure is the most common type of distribution feeder design, this dissertation focuses on the voltage profile estimation of radial distribution feeders.

Another difference between distribution systems and transmission systems is that unlike most transmission power systems, distribution power systems can contain a large amount of unbalance in the line impedance and load. Unbalanced conditions arise in normal operation when the three-phase buses have asymmetrical line current magnitudes and angles, often caused by unequal distribution of phase loads and line impedances. The unbalanced loads may cause asymmetrical voltages; although utility planners attempt to maintain balance within the distribution, the line phase structure, location of the load, and the time of use of the load typically define whether the phases of the distribution system are in balance. Many distribution lines segments are often not transposed and have higher R/X ratios than transmission systems which can also introduce unbalanced conditions [36].

Distribution systems are commonly designed with three-phase, two-phase, and single-phase power lines. It is impractical to connect every bus on the distribution system with three-phases since the additional conductors and associated infrastructure would significantly increase the installation and maintenance costs of the distribution system. Therefore, two-phase and single-phase lines are often used for loads with reduced power requirements. The use of two-phase and single-phase lines makes it more likely that unbalance conditions will occur on the distribution system because asymmetrical types of load will be connected to the different phases and the utility cannot control the electricity end user's load distribution. Similarly, it is impractical to use only single-phase lines within the distribution system. Balanced three-phase systems require less neutral conductors and deliver power with less voltage drop on the distribution lines than single-phase systems [37].

To obtain the most accurate estimation, this dissertation will use a voltage estimation technique that takes into account the unbalanced nature of the distribution system.

3.2.2 Voltage Estimation Approaches for Distribution Systems

Traditional approaches to voltage estimation have been to approximate the voltage drops within distribution feeder. Approximate voltage drop calculations assume balanced three-phase systems where the load and line impedances are symmetrically distributed over all the phases. More recent work on voltage estimation employs a state estimation approach where various algorithms are applied to determining the present states of the distribution system voltages based on measured system quantities. A brief review of some of the available voltage estimation methods is presented including the dissertation's new method utilizing the load profile data obtained in Chapter 2.

3.2.2.1 Distribution Voltage Estimation

One method to estimate the voltage values of the three-phase distribution feeder are through simple voltage calculations. K factors are an approximate method for finding the voltage drops and voltage rises along a line segment of the feeder. The K drop factor is given by Equation (3.1) and the K rise factor is given by Equation (3.2). The K drop factor is the percent voltage drop for a one mile line serving a 1 kVA balanced three-phase load. The K rise factor is the percent voltage rise for a one mile line serving a 1 kvar balanced three-phase load [38].

$$K_{drop} = \frac{V_{drop}}{V_{LN}} \quad \text{per unit drop / kVA - mi} \tag{3.1}$$

where K_{drop} is the K factor for the voltage drop,

V_{drop} is the voltage drop on the line segment,

and V_{LN} is the nominal line to neutral voltage of the line segment.

$$K_{rise} = \frac{V_{rise}}{V_{LN}} \quad \text{per unit rise / kvar - mi} \tag{3.2}$$

where K_{rise} is the K factor for the voltage rise,

V_{rise} is the voltage rise on the line segment,

and V_{LN} is the nominal line to neutral voltage of the line segment.

Equation (3.3) displays how to compute the percent voltage drop.

$$V_{\%drop} = K_{drop} \cdot kVA \cdot mi \tag{3.3}$$

where $V_{\%drop}$ is the percent voltage drop on the line segment,

K_{drop} is the K factor for the voltage drop,

kVA is the complex power of the load,

and mi is length of the line segment in miles.

Another way of approximating the voltage drop of the distribution lines is through uniformly distributed loads. In the uniformly distributed load approximation, the total load of the feeder is assumed to be equally spaced over a line segment where each modeled load is assumed to be identical with a constant current. The general equation for the total voltage drop for the uniform distributed load method is shown in Equation (3.4) [38].

$$\mathrm{Vdrop}_{\mathrm{total}} = \Re\left\{\frac{1}{2}\cdot z\cdot \ell\cdot I_T\cdot\left(1+\frac{1}{n}\right)\right\} \tag{3.4}$$

where $\mathrm{Vdrop}_{\mathrm{total}}$ is the total voltage drop on the feeder,

z is the impedance of the uniform line in Ω/mile,

ℓ is the length of the feeder,

I_T is the total current into the feeder,

and n is number of nodes and number of line sections.

When n goes to infinity in Equation (3.4), the general equation reduces to Equation (3.5) [38].

$$\mathrm{Vdrop}_{\mathrm{total}} = \Re\left\{\frac{1}{2}\cdot Z\cdot I_T\right\} \tag{3.5}$$

where $\mathrm{Vdrop}_{\mathrm{total}}$ is the total voltage drop on the feeder,

Z is the total impedance of the uniform line from the source to the end,

and I_T is the total current into the feeder.

Another approximate method is geometric load lumping where the voltage drop calculations use a constant load density distributed in various geometric patterns. This method is useful for distribution planning where determining the total load for a service area is important. Common geometric patterns include triangles, rectangles, and trapezoids [38].

The preceding approximate methods are useful for distribution planning but do not model the true system operation conditions and therefore do not address the complex operational analysis needed for distribution systems. The approximate methods assume balanced phases, known power factors, and uniform loads and therefore cannot take into account the true unbalanced environment of distribution systems.

3.2.2.2 State Estimation

Another approach to compute the voltage conditions on the feeder is through state estimation. In power systems, state estimation is the process where the unknown system states, generally the steady state bus voltage phasors, are computed using measurements from the power system. Measurements can include current flow in the system, voltage magnitudes, or power magnitudes. The main advantage of the state estimation in power systems is that the state estimator can control and identify measurement errors in metering equipment.

The most commonly used method of state estimation in power systems is the Weighted Least Squares (WLS) algorithm. The WLS algorithm computes the bus voltages states that minimize the sum of the squares of weighted deviations of estimated measurements from actual measurements. Equation (3.6) displays the weighted least-squares estimator [39].

$$\min_{\{x_1, x_2, \cdots, x_{N_s}\}} J(x_1, x_2, \cdots, x_{N_s}) = \sum_{i=1}^{N_m} \frac{\left[z_i - f_i(x_1, x_2, \cdots, x_{N_s})\right]^2}{\sigma_i^2} \tag{3.6}$$

where $J(x_1, x_2, \cdots, x_{Ns})$ is objective function for the states $\mathbf{x}$,

N_s is the number of unknown parameters,

N_m is the number of measurements,

z_i is the measured quantity,

f_i is the function relating the measurement i to the states $\mathbf{x}$,

and σ_i^2 is the variance.

One disadvantage of the WLS state estimation for distribution systems is that several redundant measurements are necessary to receive an accurate assessment of the estimated voltages. However, measurement equipment may not be available beyond the substation bus or on feeder laterals and installing additional measuring equipment can be economically impractical. Another disadvantage of conventional WLS state estimation is that it assumes that the modeled system is three-phase and balanced and therefore uses only a single-phase positive sequence model [40]. There can also be problems with convergence of the state estimation for distribution systems without measurement redundancy [41].

3.2.3 Proposed Voltage Estimation Technique Using ANN Approach

This dissertation proposes a new approach to voltage estimation on a radial distribution feeder. Essentially, forecasted load profile data is obtained from the ANNSTLF and load allocation software. With the estimated load conditions known, the forecasted load profile data is inserted into a power flow program to calculate the voltages along the feeder.

Although there will be some error in the load forecast computation, the ANN load profile forecast program offers a close approximation of the load conditions on the feeder. With the load conditions and the feeder system characteristics, there is enough information to execute a three-phase distribution power flow.

The major benefit of this technique is that the distribution power flow software can take into account the voltage unbalance on the distribution feeder and give an accurate assessment of the voltage conditions. In addition, the proposed voltage estimation method can be performed with Load Tap Changing transformers (LTC) and distribution transformers that are often difficult to model in other voltage estimation techniques. This voltage estimation technique has not been presented before in the research literature, most likely due to the inadequate knowledge of the feeder load profile values. With the more accurate load conditions developed in Chapter 2, this technique can effectively model the voltage and power flows on the feeder.

3.3 Voltage Profile Estimation Using Forecasted Data

Using the load profile and customer demand forecast that was developed in Chapter 2, an estimate of the load profile can be obtained for the feeder. Once the load profile is found from the ANN and load allocation software, the values can be inserted into the input file of a power flow program to obtain a complete description of the voltage conditions along the feeder. Sufficient care should be selected when selecting the power flow program in order to get the most accurate results. A brief discussion of the types of power flows is presented below.

3.3.1 Types of Power Flows

A power flow program, also known as a load flow program, is a software program that is commonly used in power system analysis to compute the system conditions. Power flow programs calculate the voltage magnitude and voltage angle at buses and the flow of the real power and reactive power of the power system based on the system constraints. There are two main types of power flows in use, single-phase power flows and three-phase power flows.

3.3.1.1 Single-phase Power Flow

Single-phase power flows assume that the power system is in balanced operation. As a result of this characteristic, single-phase power flows are often called balanced power flows. Single-phase power flows are often used in planning applications where long range development of the feeder is the main concern. The distribution feeder is assumed to be in balanced operation to simplify the calculations since it is difficult to predict the load makeup and unbalanced composition of the feeder in long range planning. Often, the load conditions are overestimated to give the maximum flexibility in future feeder upgrades. As a result, the voltage conditions do not reflect the true unbalanced, nonlinear environment.

In single-phase power flows, the power flow program models the positive sequence network of the distribution system through a single-phase equivalent of the system. The load is aggregated into single-phase lumped loadings and a constant voltage source is assumed on the secondary side of the substation transformer. An iterative procedure, such as using the bi-factored $\mathbf{Y}_{bus}$ admittance matrix, is then executed to calculate the bus injection currents and network voltages of the system [42].

3.3.1.2 Three-phase Power Flow

The main disadvantage of single-phase power flow programs for power system operation is that the voltages on the single-phase and two-phase laterals cannot be computed. Another disadvantage is that the single-phase power flow will not calculate the correct losses dissipated in the distribution system. Also transformer losses cannot be calculated accurately in the single-phase power flow approach [43].

Three-phase power flow programs overcome these disadvantages and thus can more accurately represent the actual conditions and losses of the distribution system. Three-phase power flows calculate the voltage conditions and flow of power of the distribution system on an individual phase basis. This allows the system conditions on unbalanced distribution systems to be calculated.

The secondary side at the substation transformer is designated the swing bus and the admittance matrix of the feeder is built for phase buses down to the secondary of the distribution transformers. Since the amount of line charging is not as significant in the distribution system as in the transmission system, the capacitance of the distribution lines is often neglected in the distribution power flow calculation.

3.3.2 Selected Power Flow

A three-phase power flow program was chosen for this dissertation due to its superior performance and ability to accurately solve unbalanced systems. Three-phase power flows are more suitable for calculating the operating voltage conditions on distribution feeders.

Given that the load profile and customer demand forecasting software is independent of the chosen three-phase power flow software, a number of choices of commercial power flow software could be considered. However, access to the software source code will be important for the optimal capacitor bank switching algorithm developed in Chapter 4. Therefore, the dissertation has chosen a three-phase power flow software originally developed by the Energy Systems Research Center at the University of Texas at Arlington. The three-phase power flow program called DLFLOW, originally developed by Sun [43], is based on an iterative bi-factored admittance matrix approach using the Gauss algorithm of forward and backward substitution. The program source code was translated from FORTRAN to the C programming language to facilitate any required modifications of the power flow program. In addition, the limit of the total number of phase buses was extended for use on distribution systems with a large number of phase buses.

3.3.3 Required Data

The voltage estimation software developed in this dissertation requires input data about the distribution system. First, system parameters such as the MVA base for the system, the nominal voltage value, and per-unit voltage of the swing bus are needed to execute the power flow program. Second, the power flow program control parameters like the voltage tolerance of the convergence, real and imaginary acceleration factors, and maximum iterations must be specified. Third, bus information is required. The bus information includes the bus number, bus phase type, bus name, initial estimate of the bus voltage magnitude and angle, total power demand on the bus, total shunt kilovars connected on the bus, and the percentage of the total demand that is on the A, B, and C phases. Finally, the line branch information must be defined. Line branch information includes the terminal bus numbers of the branch segment, branch phase type, segment line length, the line segment's nominal phase to neutral voltage, and the branch impedance data.

3.3.4 Meter Improvements to the Voltage Profile Algorithm

Similar to the load profile and customer demand forecasting program, if PLC or BPL equipment is installed at buses on the feeder then the power flow program can treat the voltage magnitude and power as a known quantities at the metered bus location. This allows the voltage magnitude estimation to become more accurate at the meter bus and the surrounding buses. Internally the power flow program converts the bus from a load bus (PQ bus) to a voltage controlled bus (PV bus). The power flow program considers the real power and voltage at the metered bus as inputs in the power flow equations and calculates the reactive power and voltage angle.

3.4 Chapter Conclusions

Electric delivery companies must minimize the cost of installing and maintaining equipment on the distribution feeder by optimizing their system performances with more intelligent monitoring and control schemes. In addition, voltage profile estimation of distribution feeder voltage conditions is important for future operation and analysis of distribution systems.

The voltage estimation algorithm discussed in this chapter is a systematic method of estimating the voltage profile of a distribution feeder with a minimum amount of monitoring equipment. The new voltage profile estimation technique employs the more accurate load profile forecasting method introduced in Chapter 2 and a three-phase power flow program to construct a per phase representation of the voltages on the distribution feeder. Using a small set of monitoring equipment, the voltage profile estimation can be used to provide better voltage regulation for distribution feeders while minimizing the overall operating cost of the distribution system. This voltage estimation method is suitable for unbalanced radial distribution feeders and can be used in applications requiring voltages at each phase bus.

As described in this chapter, a three-phase software program was extended and deployed to estimate the voltage profile using the load profile forecast of Chapter 2. The voltage profile estimation software can be used in various distribution management functions. An optimal capacitor bank switching algorithm will be developed in Chapter 4 utilizing the voltage profile estimation developed in this chapter. In Chapter 5 the results of the voltage profile estimation program is presented for an example distribution feeder.

CHAPTER 4

OPTIMAL CAPACITOR BANK SWITCHING

This chapter reviews the importance of distribution capacitor banks and past implementations of capacitor bank switching algorithms. Also, this chapter develops an optimal capacitor bank switching algorithm using the load profile and voltage profile estimations developed in Chapter 2 and Chapter 3.

4.1 Distribution System Shunt Capacitor Banks

Shunt power capacitors are widely used in distribution systems among the electric power industry. Banks of power capacitors are often used for voltage regulation and power factor correction in distribution systems. Capacitor banks are popular because of their inexpensive installation costs compared to other reactive support techniques.

4.1.1 Shunt Capacitor Banks for Voltage Regulation

Voltage regulation is an essential topic in distribution system operation. Voltage regulation for distribution feeders is the process of controlling the primary feeder voltages in order to deliver an acceptable voltage to the electricity end user during varying load states. Voltage regulation can be accomplished using substation Load Tap Changing (LTC) transformers, step voltage regulators, line voltage regulators, and switched shunt capacitor banks. Of these voltage regulation methods, switched shunt capacitor banks are of primary importance in this dissertation.

The benefit of shunt capacitor banks compared to other voltage regulators is that reactive power is supplied to the feeder during the capacitor bank's operation. The voltage levels on the feeder are influenced not only by the amount of real power delivered but also the amount of reactive power transferred. For feeders with low reactive power demands, tap changing transformers can be used to regulate the feeder voltages without reactive power resources such as capacitor banks. However, when the system is deficient in reactive power, tap changing transformers cannot control the voltages independent of reactive power support. If there is not enough reactive power at the buses, the power factor will decrease to an unacceptable lagging state and reduce the efficiency of the system.

4.1.2 Shunt Capacitor Banks for Power Factor Correction

In power factor correction, the efficiency of the power system is improved through control of local reactive power resources. Most electric loads in an AC power system require both real and reactive power to operate. While real power is useful for performing work and energy conversion, reactive power must be supplied in order for the real power to be transported over the transmission and distribution systems. To maximize the amount of real power that can be transported through the power lines, it is necessary to minimize the amount of reactive power in the transmission and distribution lines.

Distribution capacitor banks are effective in power factor correction applications since the capacitors inject reactive power into the distribution system close to the load. Generating the reactive power close to the load through the use of capacitor banks has been a common practice to reduce the amount of reactive current flowing through transmission and distribution lines. Reducing the amount of reactive current in the transmission and distribution lines is desirable because it decreases the amount of power losses that dissipate from the lines in the form of heat. This allows more real power capacity in existing power lines or permits the use of smaller, less inexpensive power lines and equipment for new installations.

4.1.3 Issues with Deploying Capacitor Banks

Maintenance costs can be a significant expense for electric utilities. Although dynamic reactive power compensation can be accomplished though synchronous condensers or Static Var Compensators (SVC), switched shunt capacitor banks are more affordable in terms of installation and maintenance costs. Yet, capacitor banks and the associated protective and control equipment must still be inspected for any physical damage or operational problems. One area where maintenance costs can be reduced is in the area of capacitor bank switching. Repeated opening and closing of the switching contacts can wear components within the capacitor banks. A more efficient capacitor bank switching schedule can increase the lifetime of the distribution system capacitor banks. Since maintenance work is time consuming and labor intensive, any reduction of usage can be economically valuable.

Coordination between shunt capacitor banks and voltage regulators is an issue for switched capacitors. Capacitor banks upstream of voltage regulator do not generally require special switching designs. However, downstream capacitor banks can interfere with upstream voltage regulators [44]. Therefore, the distribution capacitor switching software should be able to monitor upstream voltage regulators to prevent excessive change of the tap setting on the voltage regulator.

Many capacitor banks for distribution feeders are manufactured as three-phase units with single-phase capacitors connected in gounded-wye configuration for four-wire line segments. Capacitor banks are connected by either ungounded-wye or delta for three-wire line segments [44]. Three-phase capacitor banks are commonly used because single-phase capacitors are more difficult to monitor and control [35]. Also, the capacity size of single-phase capacitors is often greater than the load on many single-phase lines. Conversely, single-phase capacitor banks can establish more dynamic balancing of the distribution feeder. If single-phase capacitors are present on a feeder, an accurate method of controlling the switching schedule is needed.

4.2 Distribution System Capacitor Bank Switching

Capacitor bank switching is an important topic within power systems. Various algorithms have attempted to manage capacitor banks under a distribution management system. An overview of some of the implemented capacitor switching algorithms is presented including a new method utilizing the load profile data and voltage profile estimation from Chapter 2 and Chapter 3.

4.2.1 Capacitor Switching Methods

Several capacitor switching algorithms have been proposed over the years for use in distribution management systems. Older capacitor switching methods reduce the capacitor switching problem to a simplified model using uniformly distributed loads, uniform conductor sizes, modeling the distribution feeder as one branch, and other generalizations [45], [46]. Some methods assume that the distribution network is represented by a single radial path [47], [48]. These methods are oversimplified and do not effectively model the capacitor switching problem. Two methods of capacitor switching optimization that are presented in the literature are reviewed in this section.

One method formulates an expression for the power losses for distribution systems with lateral and sublateral branches [49]-[51]. The method endeavors to control the capacitor output current to minimize the power loss caused by the feeder load current. It determines the time variation of the capacitor output as loads are changing with time. An iterative procedure is carried out until a converged solution is achieved.

Another approach uses fuzzy set theory to construct an optimal capacitor switching dispatch schedule [52], [53]. Fuzzy sets are used to model unknown load values as trapezoidal fuzzy complex numbers. A fuzzy power flow solution is created by replacing definite variables with fuzzy variables in a forward and backward sweep calculation. A linearized programming model of the switching problem is then formed and it is solved by dual relaxation method. A disadvantage to this approach is that it assumes that the average error and maximum error at the load bus are known. The inexact load bus information could lead to less accurate calculations.

4.2.2 Proposed Implementation

A new method to capacitor bank management for radial distribution feeders is proposed in this dissertation. With knowledge of the forecasted load profile, the voltage profiles of the distribution feeder with every possible capacitor bank configuration can be estimated. A table of possible voltage profile estimations based on all the combinations of capacitor banks can be established for each hour. After the table is built, a function can iterate through the table to find the best voltage profile for the feeder based on a specified objective function.

One advantage of this technique is that each capacitor bank can be coordinated with other capacitor banks on the feeder and with voltage regulators at the substation. Instead of capacitor banks which are controlled locally with limited knowledge of the total feeder conditions, a coordinated strategy can be achieved with the capacitor banks being switched based on knowledge of the entire load distribution of the feeder.

Also, in situations where unbalanced conditions occur, the voltage profile estimation method developed in Chapter 3 can more efficiently monitor the capacitor banks by individually examining all three phases. Another advantage of using the voltage estimation technique is that it can be used to decrease the amount of maintenance on the distribution system by minimizing the number of switching operations that occur on the feeder. Switching operations can be planned over days based on the forecasted load. As discussed in Chapter 5, objectives such as switching reduction can be achieved with this method.

4.3 Optimal Capacitor Bank Switching Using Voltage Profile Estimation

The voltage profile estimation that was developed in Chapter 3 is the basis of the optimal capacitor bank switching software. As the first step, the optimal capacitor bank switching procedure incorporates a sensitivity analysis by using the impendence matrix ($\mathbf{Z}_{\text{bus}}$) of the distribution feeder. The sensitivity analysis presents a method of observing the effects of the capacitor banks on the voltage profile and quickly creating a voltage profile table of the possible voltage solutions. The sensitivity analysis is an offline procedure which will help decrease the computation time of the optimal capacitor switching algorithm. The voltage profile table contains the possible solutions for each possible capacitor configuration.

After the voltage profile table is constructed, an iteration procedure is executed to examine all the possible capacitor configurations to find the best match based on the selected objective function. Several objectives can be realized such as selecting the capacitor configurations that provides the best voltage profile for each hour; that distribute the switching changes over all the capacitor banks; or switching a favored capacitor bank on as much as practical.

Some advantages of this voltage profile estimation approach are that switching reduction can be accomplished; the capacitor banks can be better coordinated with the other capacitor banks on the feeder; and with projected voltage solutions the capacitor bank switching can be coordinated with other power system control devices. For example, the capacitor bank switching software can also coordinate the capacitor switching with load tap changers or other voltage regulators installed on the feeder.

Additionally, if single-phase capacitor banks are available, the proposed capacitor bank switching procedure can be performed on a per phase basis allowing single-phase capacitor banks to be deployed and controlled on the feeder. With the voltage table, the capacitor banks can be studied to see how each phase of the capacitor banks contributes to the voltage profile, which is not easily done with the present capacitor switching software. The software also has the potential to examine how the loss of one phase of a three-phase capacitor bank will affect the voltage profile.

4.3.1 Sensitivity Analysis

The capacitor bank switching algorithm uses sensitivity analysis and the impedance matrix of the feeder to form an array of potential impact on the voltage profiles. A brief explanation of the sensitivity analysis procedure is presented below.

The sensitivity equations are written in vector form in Equation (4.1).

$$g(\mathbf{x},\mathbf{u}) = 0 \tag{4.1}$$

where $\mathbf{x}$ are the dependent variables,

and $\mathbf{u}$ are the independent or control variables.

Let $u \rightarrow u + \Delta u$. Since x is dependent on the control variable u, x must change into: $x \rightarrow x + \Delta x$ to satisfy the equations: $g(x + \Delta x, u + \Delta u) = 0$ [54].

In matrix format and solving for $x + \Delta x$:

$$\begin{bmatrix} x_1 + \Delta x_1 \\ x_2 + \Delta x_2 \\ \vdots \\ x_n + \Delta x_n \end{bmatrix} = \begin{bmatrix} S_{1,1} & S_{1,2} & \cdots & S_{1,m} \\ S_{2,1} & S_{2,2} & \cdots & S_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n,1} & S_{n,2} & \cdots & S_{n,m} \end{bmatrix} \cdot \begin{bmatrix} u_1 + \Delta u_1 \\ u_2 + \Delta u_2 \\ \vdots \\ u_m + \Delta u_m \end{bmatrix} \tag{4.2}$$

where x_i are the dependent variables,

$\mathbf{S}$ is the sensitivity matrix,

and u_i are the independent or control variables.

Isolating the delta change variables:

$$\begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ \vdots \\ \Delta x_n \end{bmatrix} = \begin{bmatrix} S_{1,1} & S_{1,2} & \cdots & S_{1,m} \\ S_{2,1} & S_{2,2} & \cdots & S_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n,1} & S_{n,2} & \cdots & S_{n,m} \end{bmatrix} \cdot \begin{bmatrix} \Delta u_1 \\ \Delta u_2 \\ \vdots \\ \Delta u_m \end{bmatrix} \tag{4.3}$$

or

$$\Delta \mathbf{x} = [\mathbf{S}_\theta] \cdot \Delta \mathbf{u} \tag{4.4}$$

The (i,j) element of $\mathbf{S}_\theta$, ($S_{i,j}$), is the value of change in x_i when u_j increases its value by 1 p.u. with the other control variables unchanged. If the sensitivity matrix is $\mathbf{S}_\theta = \mathbf{Z}_{bus}$, the dependent variables are $\Delta \mathbf{x} = \Delta \mathbf{v}$, and the independent variables are $\Delta \mathbf{u} = \Delta \mathbf{i}$ then Equation (4.3) becomes Equation (4.5).

$$\begin{bmatrix} \Delta v_1 \\ \Delta v_2 \\ \vdots \\ \Delta v_n \end{bmatrix} = \begin{bmatrix} Z_{1,1} & Z_{1,2} & \cdots & Z_{1,n} \\ Z_{2,1} & Z_{2,2} & \cdots & Z_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{n,1} & Z_{n,2} & \cdots & Z_{n,n} \end{bmatrix} \cdot \begin{bmatrix} \Delta i_1 \\ \Delta i_2 \\ \vdots \\ \Delta i_n \end{bmatrix} \tag{4.5}$$

or

$$\Delta \mathbf{v} = \left[\mathbf{Z}_{\text{bus}} \right] \cdot \Delta \mathbf{i} \tag{4.6}$$

The (i,j) element of $\mathbf{Z}_{\text{bus}}$, ($Z_{i,j}$), is the value of change in the voltage v_i when the current i_j increases its value by 1 p.u. with the other control variables unchanged. The elements of impedance matrix show the effect a change in the current at a bus has on the change in bus voltage.

The effect of a capacitor bank on the change in the voltage profile can be observed by using Equation (4.5). The change in current can be viewed as the capacitor bank injection current which is calculated from the rated kvar value of the capacitor bank and an assumed voltage reference. Multiplying the capacitor bank injection current by the associated column in the bus impedance matrix will give the change in voltage along the feeder.

Although the impedance sensitivity method is a linearized model and does not provide an exact solution, it does provide an immediate way of evaluating the effect of the voltage change within an acceptable tolerance. The advantage of the impedance sensitivity method is that it increases the calculation speed of the capacitor bank combination table since only one power flow must be run for the hour. Otherwise multiple power flows must be run to create the table for each hour. The sensitivity table procedure significantly reduces the computation time of the different combinations of capacitor bank switching since it involves multiplying and adding arrays compared to iterating through many different power flow solutions. This can save considerable time especially when considering multiple feeders from a substation or controlling multiple capacitor banks.

4.3.2 Voltage Profile Table

The next step in the optimal capacitor bank switching procedure is to obtain the hourly load forecasts for the feeder. At a predetermined time of the day, the ANNSTLF will forecast the hourly load on the feeder for the entire day, resulting in 24 different hourly load values. The power flow is then run for each hour with no capacitors online to obtain a base case for each hour. After the base cases are calculated, the hourly base cases and each row in the change-of-voltage sensitivity table are added together. Equation (4.7) indicates this procedure. This results in 2^n (including the base case with no capacitors) different combinations of voltage estimation profiles for each hour of the day for n capacitor banks and two levels (ON/OFF).

$$V_{est} = V_{base} + \Delta V \tag{4.7}$$

where V_{est} is the voltage profile estimate,

V_{base} is the power flow solution with no capacitor banks online,

and ΔV is the change in voltage due to the capacitor bank.

The power flow software could be executed for each case of the voltage table; however, the computation time would be significantly higher than the calculation with the sensitivity matrix. For example, a feeder with seven capacitor banks will have 128 combinations of capacitor configurations for each hour when considering only ON/OFF states. Every hour, 128 power flows would need to be executed to calculate the voltage table for the ON/OFF states. For capacitor banks with different voltage settings, additional power flows would be required.

With the sensitivity matrix, only one power flow, the base case, is required to be executed. The remaining configurations are calculated using Equation (4.5) and Equation (4.7). The voltage table is calculated in an offline procedure and does not need to be recalculated unless the feeder is reconfigured or there is a change in the line impedance values.

Table 4.1 displays an example voltage table of the switching possibilities of each capacitor configuration for a sample distribution feeder. Each row in the table represents the switching configuration of the voltage estimate. For example, row 9 contains the change in voltage along the feeder when capacitor bank one is ON, capacitor bank four is ON, and the remaining capacitor banks are OFF.

The system impedance matrix of the distribution feeder can be built by either inverting the system $\mathbf{Y}_{\text{bus}}$ or by formation of the $\mathbf{Z}_{\text{bus}}$ one step at a time [37]. With the rise in computing power and system memory, taking the inverse of the $\mathbf{Y}_{\text{bus}}$ for a distribution feeder is not as impracticable as in years past. If the feeder is reconfigured, the system impedance matrix must be rebuilt.

Table 4.1: Voltage Profiles for Each Switching Possibility

Row	Configuration	Bus 1	Bus 2	Bus 3	Bus 4	Bus 5	⋯	Bus n
1	0000001	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
2	0000010	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
3	0000011	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
4	0000100	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
5	0000101	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
6	0000110	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
7	0000111	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
8	0001000	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
9	0001001	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱	⋮
127	1111111	V_{est}	V_{est}	V_{est}	V_{est}	V_{est}	⋯	V_{est}

4.3.3 Switching Procedure

With the different combinations of voltage estimation profiles calculated, the next step is to compute the occurrence of the number of hours each capacitor switching scheme has within the acceptable voltage profile band. Profiles can be removed from a tracking array if they do not conform to a specified voltage band. If there are sequences that conform to the voltage band for all hours in the day, then one of these sequences can be chosen based on matching the previous day's final sequence or based on a sequence with fewest capacitors online.

For sequences with less than 24 hours that conform to the voltage band, the sequences that retain the most hours of the day during the peak load time of the day are good selections for a base sequence. The hours of the day that do not have any sequences in the tracking array can be reprocessed with a different voltage band for less optimal solutions.

The voltage band can be reduced to a narrower voltage profile band if there are too many acceptable solutions for the entire day. Similarly, the voltage band can be increased to a wider voltage profile band if there are no solutions that satisfy the predefined conditions. Sufficient care should be taken to insure that the acceptable band does not exceed the maximum voltage deviations allowed on the feeder. Other operation requirements such as reduced voltage operation can also be accommodated.

Once all hours of the day have sequences in the tracking array that conform to the acceptable voltage levels, the tracking array will normally have several voltage profiles for each hour. There are different options available to select an appropriate capacitor bank configuration from the tracking array based on different objectives.

The first option is to select capacitor configurations that reduce the amount of switching through the day. This option finds capacitors sequences that have consecutive hours without a capacitor state change.

A second option is to keep track of all switching operations and select capacitor configurations that distribute the switching over all capacitor banks. This option attempts to reduce the amount of switching, but also evenly distributes the wear on the capacitor banks. If one capacitor bank is switched online then its switching priority is reduced in the selection process. If more reactive support is required then a higher priority capacitor bank is chosen so that the switching operations are evenly distributed all over all capacitor banks.

A third option is to select capacitor configurations that switch a favored capacitor bank on as much as possible. This option is the opposite of the second option and attempts to assign as much wear on one capacitor bank so that the utility only has to service the selected capacitor banks.

The fourth option is to select the capacitor configurations that provide the best voltage profile for each hour. In this method, reducing the amount of switching on the capacitor banks is not the main objective; instead the voltage profile that produces least change from the nominal voltage is selected. This is an important feature for reduced voltage operation for possible load reduction scenarios.

The binary number of the chosen row number is the estimated switching sequence of capacitor banks. As a final step, the power flow can be executed to confirm the chosen switching sequences conform to the voltage band. Refer to Figure 4.1 for an analysis flowchart.

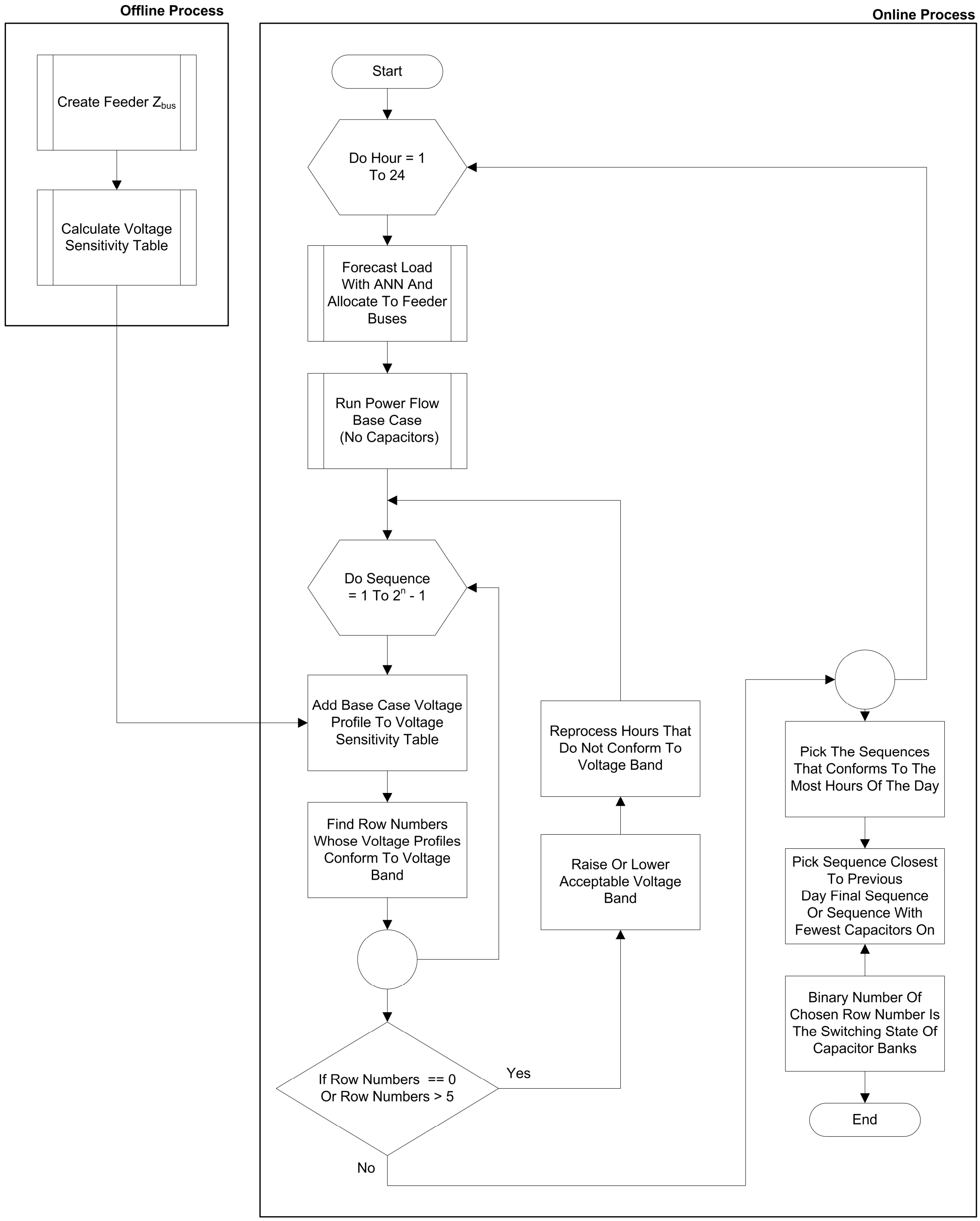

Figure 4.1: Capacitor Bank Switching Analysis Flowchart.

4.3.4 Locating New Monitoring Equipment and Capacitor Banks

In addition to the capacitor bank switching sequence, examining the elements of the impedance matrix with a load proportional change in current, the best locations for deploying new voltage monitoring equipment and capacitor banks can be determined. The bus that produces the largest change in voltage due to the impedance structure can be observed from the previously discussed sensitivity method. Since the bus with the largest change in voltage will contain the largest uncertainty in the voltage estimation, a bus with a large voltage change due to the load will be a good location for new monitoring equipment in order to remove the voltage estimation's uncertainty at that bus.

An iteration procedure can be implemented to search through all the possible change in voltage arrays to find the largest uncertainty in the voltage profile estimation. Buses that already contain monitoring equipment or buses without adequate utility pole space can be excluded in the iteration procedure.

Similarly, capacitor banks can be located using the impedance matrix by examining the voltage change in the sensitivity analysis. Essentially, each column of the impedance matrix is compared to see which column number (bus location) produces the best change in the feeder voltage profile.

4.3.5 Required Data

The required data for the optimal capacitor bank switching algorithm includes the size, location, and number of capacitor banks on the distribution feeder. Also information on whether the capacitor banks are single-phase or three-phase controlled can be useful in balancing the system voltages. The locations of the underground and overhead branches and buses are needed for the function of minimizing the switching on underground feeders.

4.4 Minimize Switching and Installation of Underground Capacitors

Most capacitor banks installed in distribution systems are pole mounted on overhead lines [44]. Less common in distribution systems are padmounted capacitors which can be used for underground conductors.

While underground distribution systems are less common, the use of underground conductors for portions of the distribution system is growing. More urban and suburban developments are requiring inconspicuous distribution lines for aesthetic reasons and at the same time there is less overhead space for distribution equipment. Reliability also can be increased with underground lines since fewer faults occur due to tree limbs, animals, or traffic accidents.

Nevertheless, the cost to install and operate capacitor banks in the underground distribution system is higher than its counterpart in the overhead distribution system. It is therefore useful to minimize the number of padmounted capacitor banks in mixed overhead and underground distribution systems. The objective is to provide the necessary voltage support for the feeder while reducing or even eliminating the need to install reactive resources in the underground portion of the feeder. To accomplish this goal, the capacitor bank switching algorithm can be expanded to include support for underground feeders.

Before running the optimal capacitor switching software, the underground and overhead buses are specified in an input file. In the optimal capacitor bank switching algorithm's iteration procedure preference to switching is given first to capacitor banks that are on the overhead portion of the feeder.

Similar to specifying the location of new capacitor banks in Section 4.3.4, the sensitivity impedance matrix can be used to find locations suitable for new installations of capacitor banks in mixed overhead and underground distribution systems. The capacitor bank location function gives preference to buses on the overhead portion of the feeder that have the greatest effect on the voltages in the underground portion of the feeder.

4.5 Chapter Conclusions

Reactive power control is essential for improving the efficiency and reliability of distribution power systems. Capacitor banks are often used to provide reactive power near the load and for voltage regulation. Electric delivery companies can minimize the cost of managing and maintaining capacitor banks on the distribution feeder by optimizing the switching schedule with more intelligent control software. A more efficient method to switch the available capacitor banks onto the distribution power system can increase the system reliability.

Instead of switching capacitor banks in a predefined order or using local controllers near the capacitor banks, the proposed capacitor switching algorithm develops a centralized capacitor management approach based on an estimate of the distribution system voltage profile. Whereas local capacitor bank controllers switch based on their local conditions, the proposed capacitor switching scheme takes a proactive approach and considers the entire voltage profile throughout the day in order to coordinate all the capacitors to achieve the desired objective functions.

Using the voltage profile estimation algorithm developed in Chapter 3, a table of the possible voltage profiles is computed. An iteration procedure is then applied to find the best capacitor configuration. A sensitivity analysis is performed using the impedance matrix to improve the calculation speed of the iteration procedure. Several objectives can be selected such as minimizing switching with evenly distributed wear; switching a favored capacitor bank online more often; or selecting the best voltage profile for each hour. Also, the iteration function can minimize the switching on underground conductors to reduce or even eliminate the need to install reactive resources in the underground portion of the feeder.

This chapter presented a power system application using the distribution load forecasting software developed in Chapter 2 and the voltage estimation technique described in Chapter 3. In Chapter 5, the results of the optimal capacitor bank switching software is demonstrated for a sample distribution feeder.

CHAPTER 5

ALGORITHM VALIDATION

This chapter validates the proposed algorithms by applying the load profile and customer demand forecasting program, voltage estimation program, and capacitor bank switching program to a sample system from a local utility.

5.1 Sample System

A 12.47 kV radial feeder from a local utility with a combination of residential, commercial, and industrial loads was selected to demonstrate the effectiveness of the proposed algorithms. Figure 5.1 displays the simplified one-line diagram of the feeder and the locations of the loads. The feeder has a mixture of single-phase, two-phase, and three-phase buses with 343 numbered buses or 766 phase-buses (187 three-phase buses, 49 two-phase buses, and 107 single-phase buses). For simplicity, some intermediate buses with no load were omitted in the one-line diagram.

There are 83 load buses with single-phase, two-phase, and three-phase loads. The bus numbers do not always indicate a sequential location along the feeder. After the original bus numbering was established, as new buses were added to the feeder, the new bus with the next sequential number could be placed at any location along the feeder. Seven three-phase capacitor banks are located along the feeder. A solid circle in Figure 5.1 denotes a capacitor bank location.

Figure 5.2 shows the hourly load from February 9, 2004 to August 1, 2006 for the sample feeder. Temperature data in Celsius for each hour is display in Figure 5.3. Hours containing bad data were omitted from Figure 5.2 and Figure 5.3. The feeder is located in the North Texas region.

Figure 5.4 displays the hourly total load at the substation for a Thursday July 8, 2004 and Monday January 10, 2005. Figure 5.5 illustrates the hourly phase current at the substation for the same days as Figure 5.4.

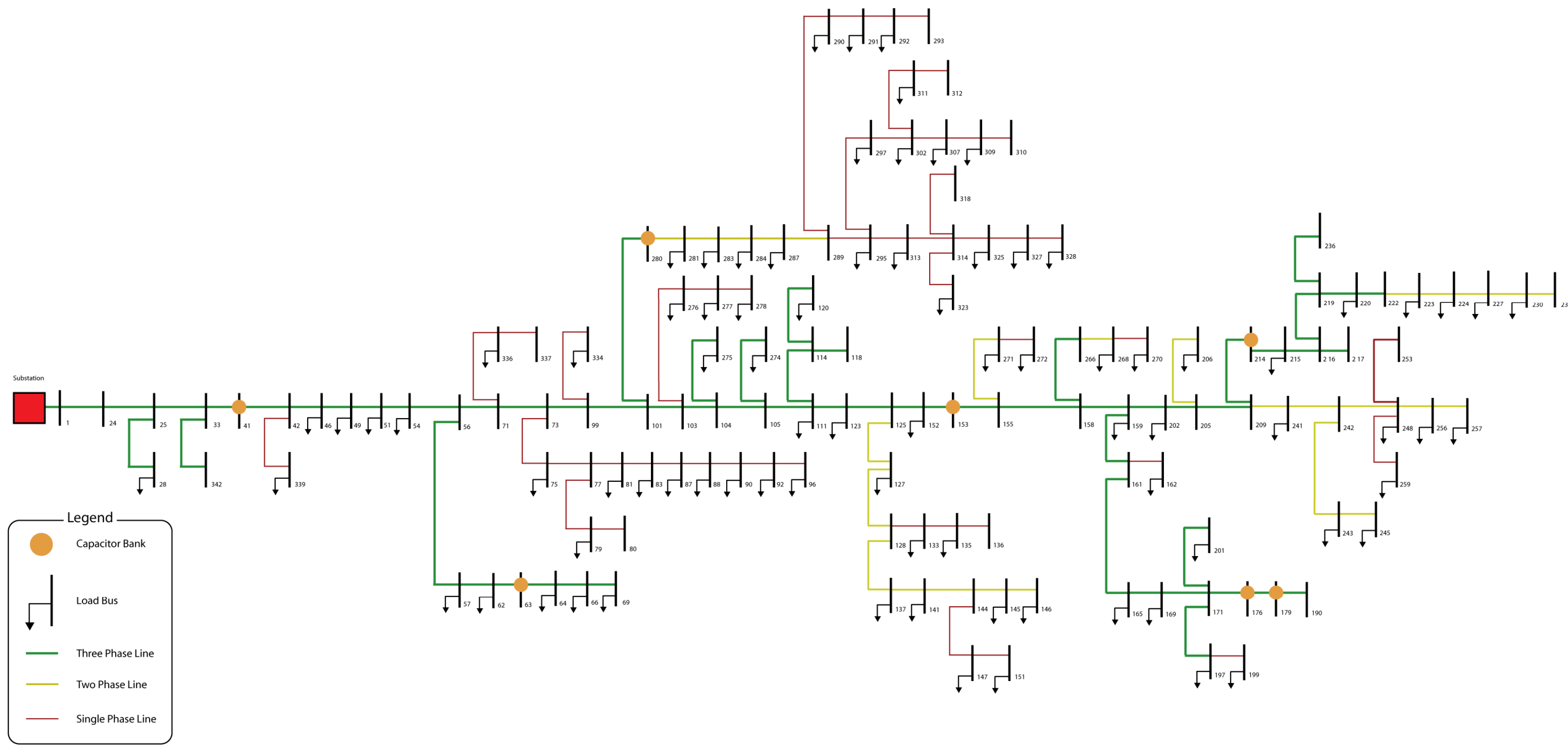

Figure 5.1: Sample 12.47 kV Radial Feeder Diagram.

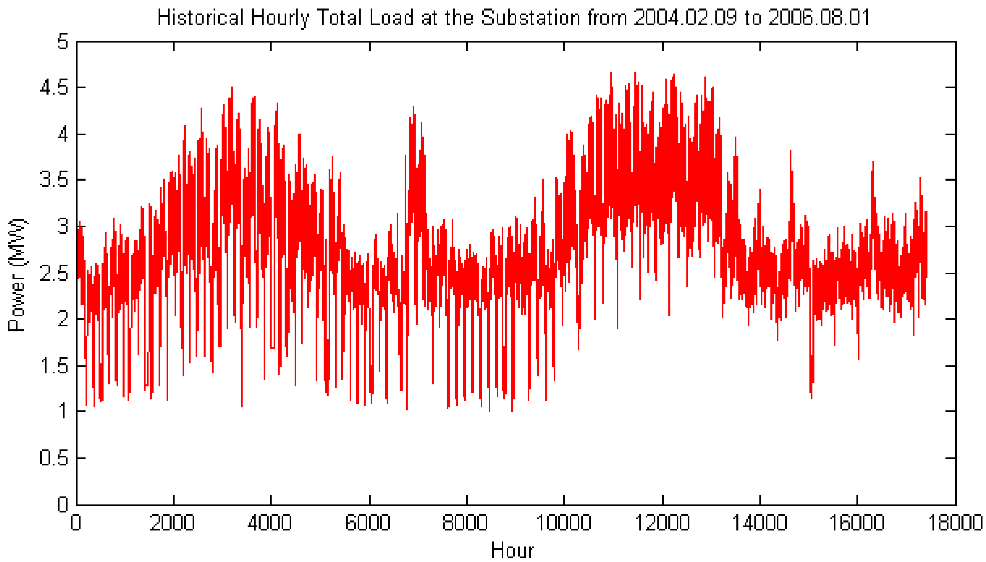

Figure 5.2: Hourly Load at the Substation from February 9, 2004 to August 1, 2006.

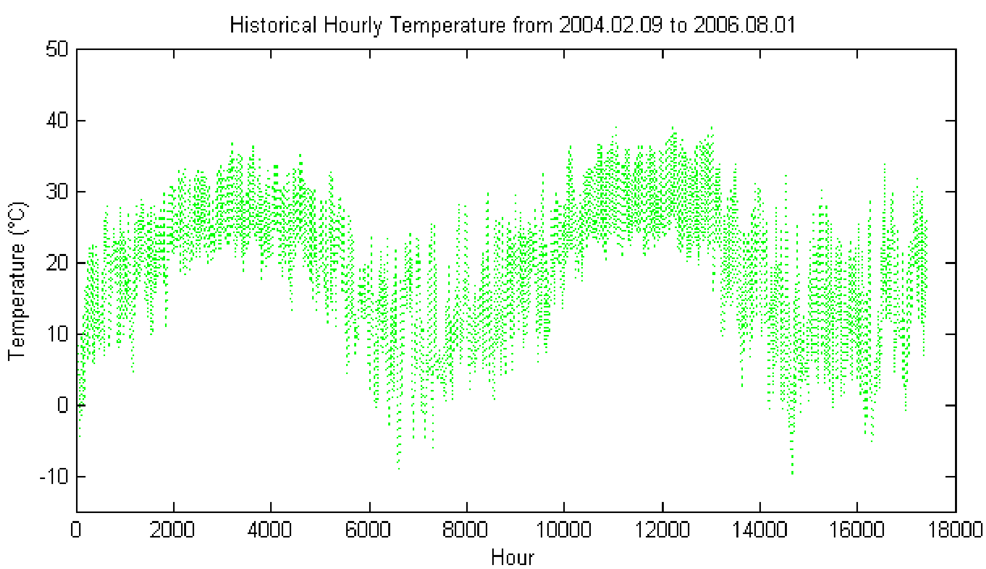

Figure 5.3: Hourly Temperature from February 9, 2004 to August 1, 2006.

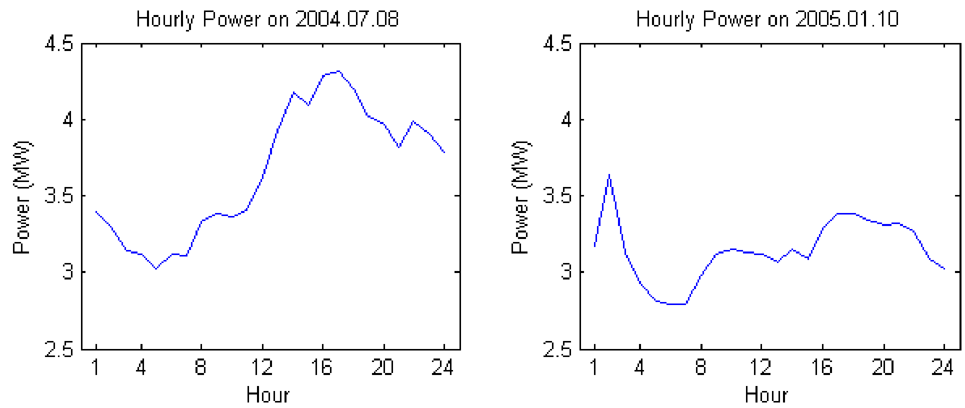

Figure 5.4: Hourly Total Load at the Substation for a Day in Summer and a Day in Winter.

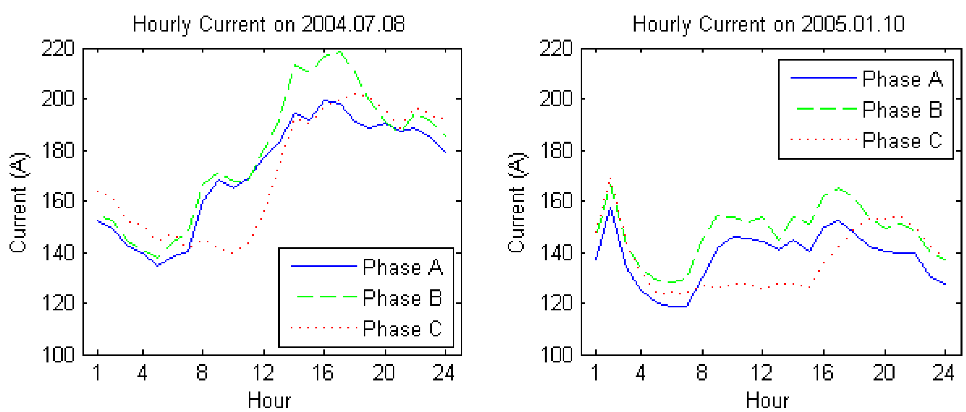

Figure 5.5: Hourly Phase Current at the Substation for a Day in Summer and a Day in Winter.

5.2 Load Profile and Customer Demand Forecasting Performance

This section presents the performance of the load profile and customer demand forecasting software that was introduced in Chapter 2. To begin, the ANNSTLF software was trained with two years of historical load and weather information. The ANNSTLF software contains twenty different neural networks and each neural network was trained with data in the time range for that network type. In the training procedure, incorrect and missing data were omitted from the training data set. After training, the ANNSTLF weights were stored into a database for the testing stage.

The ANNSTLF software was tested for two days with historical information that were not included in the training data set. Hour ahead forecasts were executed for the two test days, Sunday June 11, 2006 and Wednesday June 21, 2006. These are summer days where it is important to have a high degree of accuracy of the load forecast. Table 5.1 and Table 5.2 display the results from the ANNSTLF for each test day.

Table 5.1: Actual and Forecasted MW Load Comparison for Sunday June 11, 2006

Date	Day	Hour	Network Type	Actual Value	Forecasted Value	Difference	Percent Difference
6/11/2006	Sunday	1	15	3.5406	3.7943	-0.2537	7.1655
6/11/2006	Sunday	2	15	3.4023	3.6379	-0.2356	6.9247
6/11/2006	Sunday	3	15	3.2030	3.4887	-0.2857	8.9198
6/11/2006	Sunday	4	15	3.2625	3.3602	-0.0977	2.9946
6/11/2006	Sunday	5	15	3.2671	3.2839	-0.0168	0.5142
6/11/2006	Sunday	6	16	3.1260	3.2150	-0.0890	2.8471
6/11/2006	Sunday	7	16	3.1043	3.1907	-0.0864	2.7832
6/11/2006	Sunday	8	16	3.2310	3.1855	0.0455	1.4082
6/11/2006	Sunday	9	17	3.5218	3.2537	0.2681	7.6126
6/11/2006	Sunday	10	17	3.7514	3.4071	0.3443	9.1779
6/11/2006	Sunday	11	17	3.7937	3.5737	0.2200	5.7991
6/11/2006	Sunday	12	17	3.9897	3.7642	0.2255	5.6521
6/11/2006	Sunday	13	17	4.0142	3.8890	0.1252	3.1189
6/11/2006	Sunday	14	17	4.0656	3.9650	0.1006	2.4744
6/11/2006	Sunday	15	17	3.9982	4.0162	-0.0180	0.4502
6/11/2006	Sunday	16	17	3.9895	4.0157	-0.0262	0.6567
6/11/2006	Sunday	17	18	4.1452	4.0495	0.0957	2.3087
6/11/2006	Sunday	18	18	3.9531	4.0209	-0.0678	1.7151
6/11/2006	Sunday	19	18	4.0291	4.0299	-0.0008	0.0199
6/11/2006	Sunday	20	18	3.9596	4.0220	-0.0624	1.5759
6/11/2006	Sunday	21	18	3.9650	3.9772	-0.0122	0.3077
6/11/2006	Sunday	22	19	3.9175	3.9494	-0.0319	0.8139
6/11/2006	Sunday	23	19	3.7314	3.9215	-0.1901	5.0946
6/11/2006	Sunday	24	19	3.5483	3.8008	-0.2525	7.1161

Average Error	1.2578
MAPE	3.6438

Table 5.2: Actual and Forecasted MW Load Comparison for Wednesday June 21, 2006

Date	Day	Hour	Network Type	Actual Value	Forecasted Value	Difference	Percent Difference
6/21/2006	Wednesday	1	5	3.0909	3.3006	-0.2097	6.7844
6/21/2006	Wednesday	2	5	3.0748	3.1497	-0.0749	2.4359
6/21/2006	Wednesday	3	5	3.0706	3.0458	0.0248	0.8077
6/21/2006	Wednesday	4	5	2.8713	3.0089	-0.1376	4.7923
6/21/2006	Wednesday	5	5	2.9112	2.9548	-0.0436	1.4977
6/21/2006	Wednesday	6	6	2.8995	2.9232	-0.0237	0.8174
6/21/2006	Wednesday	7	6	2.8925	2.9952	-0.1027	3.5506
6/21/2006	Wednesday	8	6	3.3863	3.1026	0.2837	8.3779
6/21/2006	Wednesday	9	7	3.4497	3.2265	0.2232	6.4701
6/21/2006	Wednesday	10	7	3.5426	3.3543	0.1883	5.3153
6/21/2006	Wednesday	11	7	3.5256	3.5339	-0.0083	0.2354
6/21/2006	Wednesday	12	7	3.7835	3.6015	0.1820	4.8104
6/21/2006	Wednesday	13	7	3.7189	3.7114	0.0075	0.2017
6/21/2006	Wednesday	14	7	4.0123	3.8287	0.1836	4.5759
6/21/2006	Wednesday	15	7	4.1234	3.9527	0.1707	4.1398
6/21/2006	Wednesday	16	7	4.1461	3.9989	0.1472	3.5503
6/21/2006	Wednesday	17	8	4.0047	4.0330	-0.0283	0.7067
6/21/2006	Wednesday	18	8	3.8842	4.0195	-0.1353	3.4833
6/21/2006	Wednesday	19	8	3.9584	3.9607	-0.0023	0.0581
6/21/2006	Wednesday	20	8	3.8426	3.9291	-0.0865	2.2511
6/21/2006	Wednesday	21	8	3.9714	3.9131	0.0583	1.4680
6/21/2006	Wednesday	22	9	3.8054	3.8114	-0.0060	0.1577
6/21/2006	Wednesday	23	9	3.5048	3.7405	-0.2357	6.7251
6/21/2006	Wednesday	24	9	3.4080	3.6696	-0.2616	7.6761

Average Error	0.4712
MAPE	3.3704

From the tables, the Mean Average Percent Error (MAPE) is low and the ANNSTLF performs well when forecasting the total load at the substation. Typical MAPE values for load forecasting are within 1-8 %. Figure 5.6 and Figure 5.7 compare the forecasted load to the actual load for each test day.

After the forecasted load is calculated, the total load is allocated out to each load bus as described in Section 2.3.2. The forecasted load profile of the load allocation software for the test day Sunday June 11, 2006 at hour 13 is shown in Figure 5.8. Figure 5.9 displays the forecasted load profile of the load allocation software for the test day Saturday June 21, 2006 at hour 21.

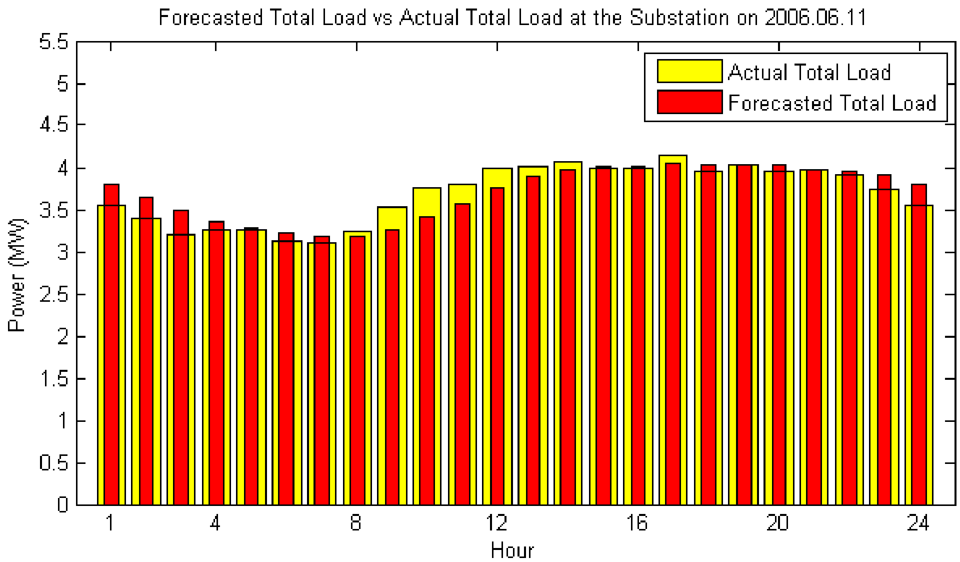

Figure 5.6: Total Load Forecast Comparison for Sunday June 11, 2006.

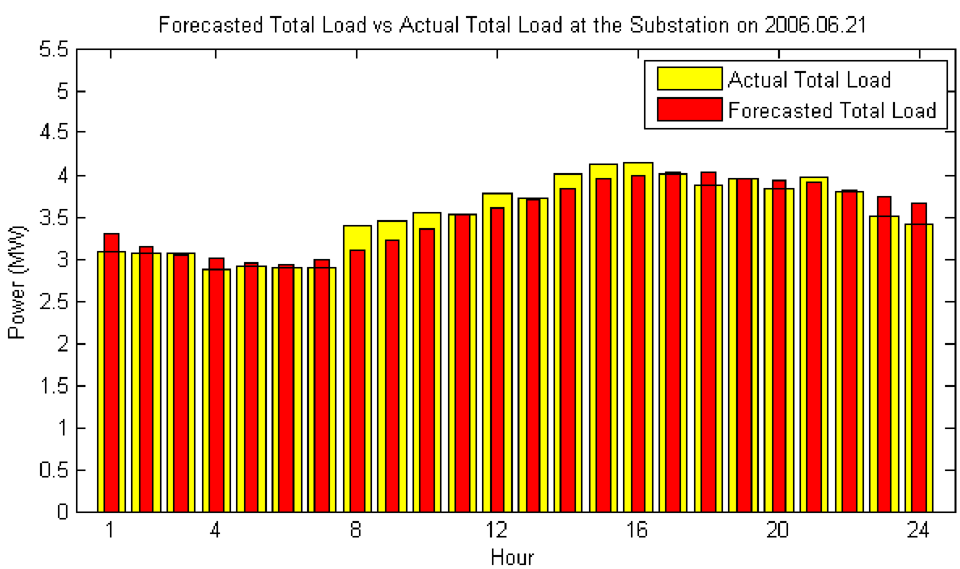

Figure 5.7: Total Load Forecast Comparison for Wednesday June 21, 2006.

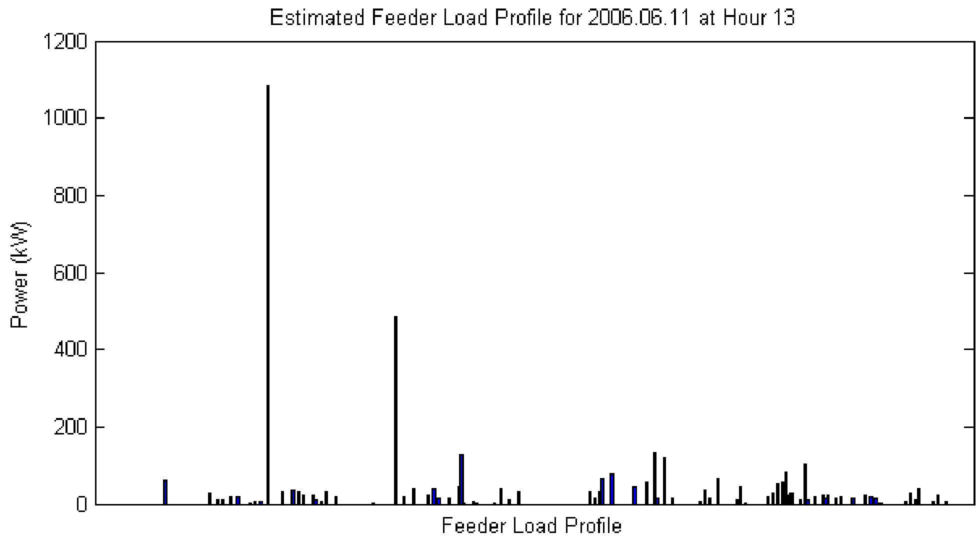

Figure 5.8: Load Profile for Sunday June 11, 2006 at Hour 13.

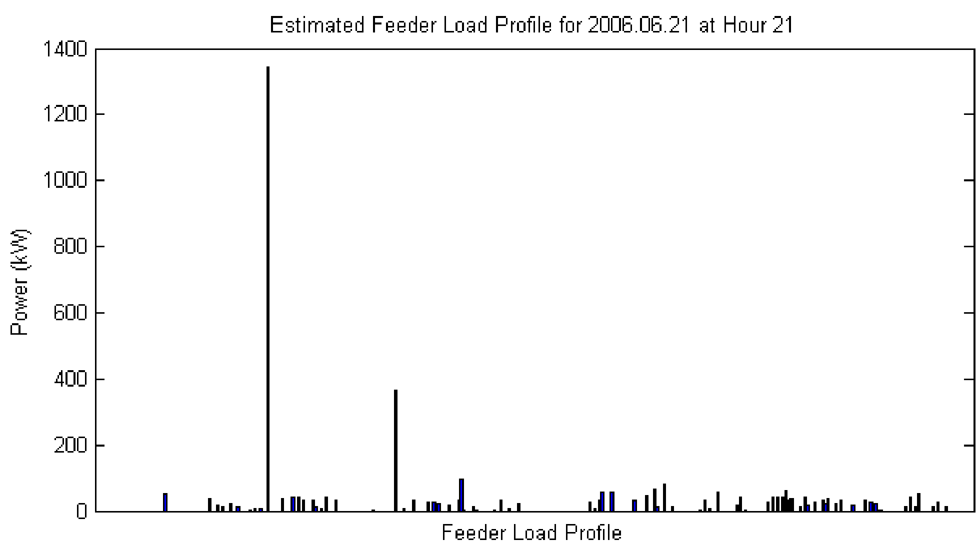

Figure 5.9: Load Profile for Wednesday June 21, 2006 at Hour 21.

5.3 Voltage Profile Estimation Performance

The voltage profile estimation method was described in Chapter 3. This section displays the output of the voltage profile estimation software. Figure 5.10 shows the estimated voltage profile of the feeder for Sunday June 11, 2006 at hour 13 which is the same test day selected for the load profile forecast example in Section 5.2. Each voltage phase is plotted separately in Figure 5.10. Figure 5.11 displays the estimated voltage profile of the feeder for Saturday June 21, 2006 at hour 21.

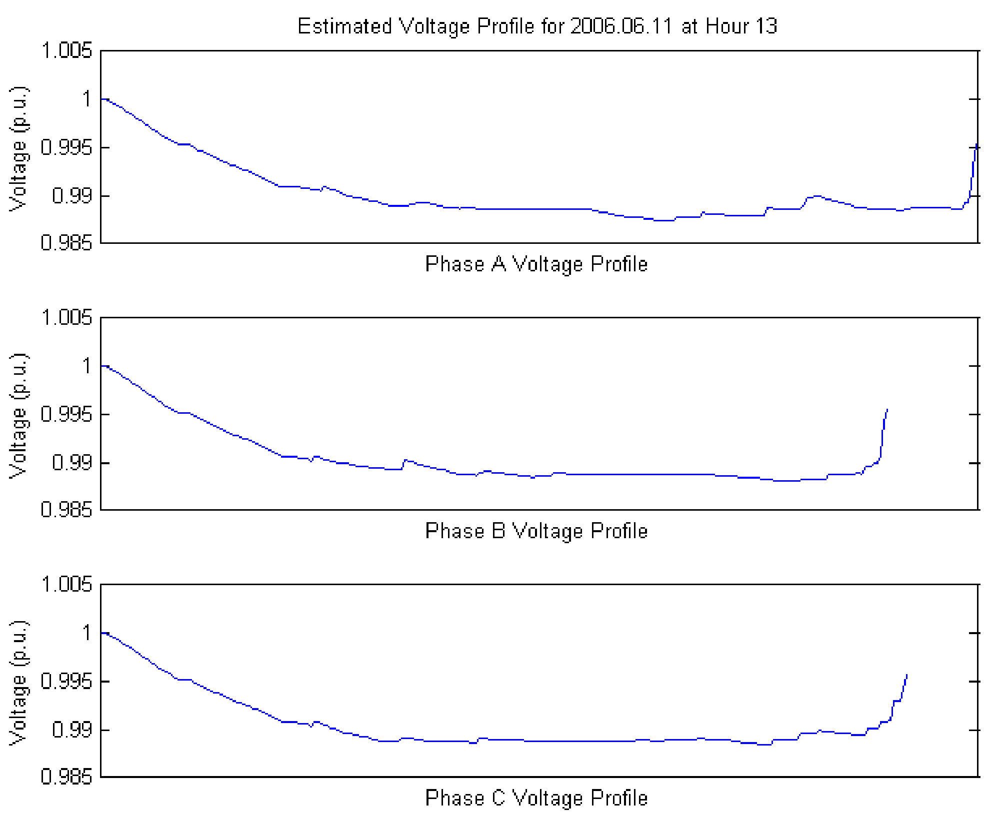

Figure 5.10: Voltage Profile for Sunday June 11, 2006 at Hour 13.

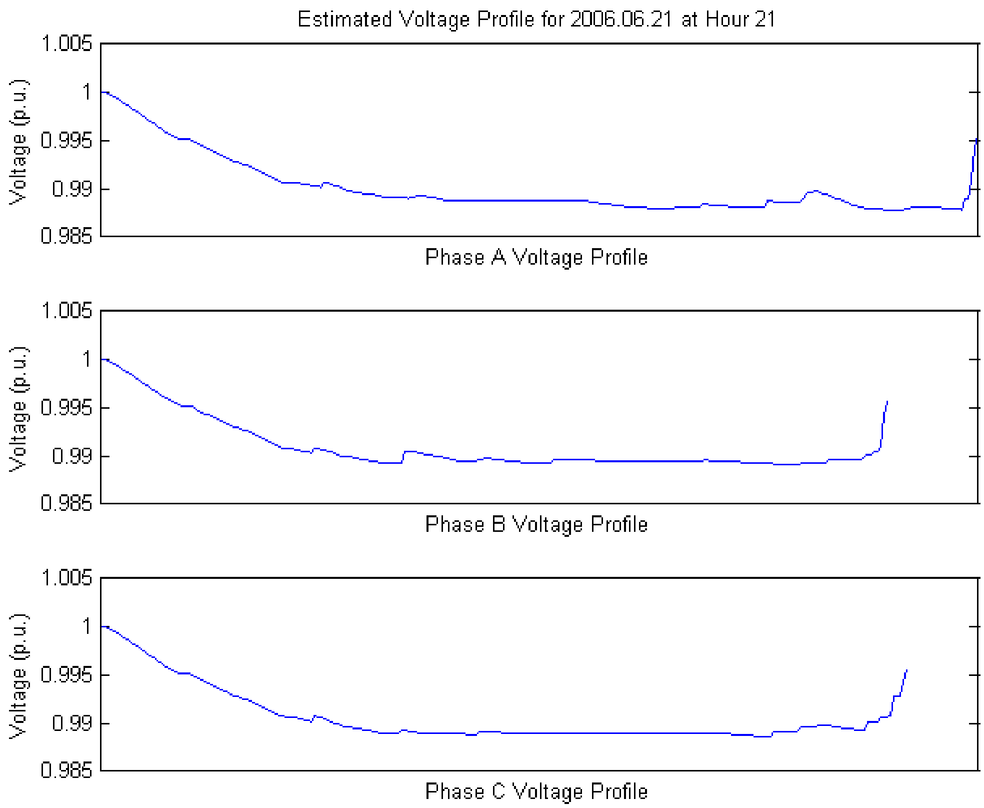

Figure 5.11: Voltage Profile for Wednesday June 21, 2006 at Hour 21.

There are 272 phase A buses, 244 phase B buses, and 250 phase C buses on the sample feeder which accounts for the different plot lengths in Figures 5.10 and Figure 5.11. The voltage increases at the end of the profiles because of the non-sequential bus numbering scheme used on the distribution feeder and the lateral structure of the feeder. The last few phase buses where the voltage appears to increase are located on lateral segments near the substation at the beginning of the feeder, as discussed in Section 5.1.

5.4 Optimal Capacitor Bank Switching Performance

A study of the benefit of capacitor bank switching scheme for the sample distribution system is presented in this section. The optimal capacitor bank switching algorithm was discussed in Chapter 4. To begin the switching study, first the $\mathbf{Z}_{\text{bus}}$ of the sample feeder was obtained and multiplied by the modeled capacitor injection current to determine a sensitivity matrix. A change-in-voltage table was then created by multiplying the associated $\mathbf{Z}_{\text{bus}}$ columns with all the possible combinations of the capacitor injection current.

The next step was to execute the ANNSTLF to generate a day's worth of hourly forecasted load values and then allocate out the forecasted load values to the buses for the hourly feeder load profiles.

In order to show the performance to different objective functions, two examples of the capacitor switching algorithm are studied in Section 5.4.1 and Section 5.4.2. Section 5.4.1 will show a capacitor bank switching situation for voltage performance where only one capacitor bank is needed for the entire day. The algorithm will find the best capacitor bank on the feeder to switch online. Section 5.4.2 will present a capacitor bank switching situation for switching reduction for a simulated extreme day where more capacitor bank switching is required on the feeder. The capacitor bank switching sequence that provides the minimum number of switching changes for the day will be selected by the optimal capacitor bank switching algorithm. For each case, the performance of the capacitor switching algorithm is compared to another method where the capacitors are switched online in a predetermined order without forecasted knowledge.

For each section, several voltage profiles were generated using the hourly feeder load profiles and a three-phase power flow program. These voltage profiles were considered base cases since no capacitors were switched online in the input files. The base case voltage profiles were added to the change-in-voltage table to obtain the estimated voltage profiles for all combinations of the capacitor banks.

5.4.1 Capacitor Switching for Voltage Performance

Figure 5.12 shows a comparison between the estimated voltage profile found using the change-in-voltage table plus a base case and another voltage profile calculated using the three-phase power flow program. As can be seen in Figure 5.12, the estimated voltage profile has a similar curve to the power flow solution.

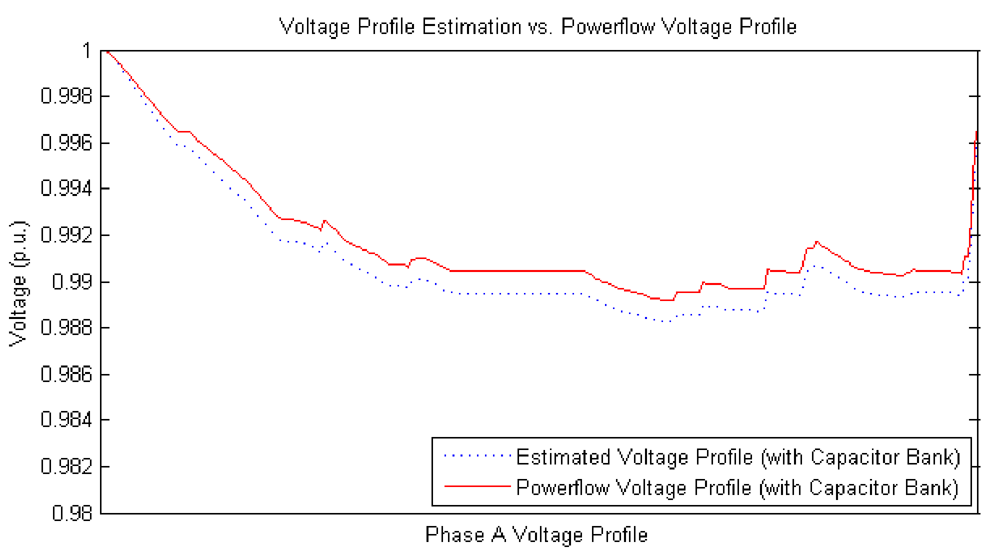

Figure 5.12: Phase A Voltage Profile Comparison.

Again, the voltage increase at the end of the profile is due to the bus number scheme, as discussed in Section 5.1. Although it is not an exact match to the power flow solution, the estimated voltage profile does follow the power flow solution closely and offers a sufficient way of evaluating the effect of the capacitor banks.

Figure 5.13 shows the 24 hour curves for two cases, without any capacitor banks online and with all the capacitor banks online. The lower 24 hour curves in Figure 5.13 are the base voltage profiles where no capacitors are online. The upper 24 hour curves in Figure 5.13 are the voltage profiles for the case with all seven of the capacitors online. Together, Figure 5.13 illustrates the potential range of the voltages for each phase. From the phase subplots, it appears that each phase's voltage should be raised; however, using seven capacitors would raise the voltage too high.

With the estimated voltage profiles calculated from the change-in-voltage table, the next step was to apply an iteration procedure to find a suitable solution. The algorithm's objective was to select capacitor configurations for each hour of the day that provides the best voltage profile voltage while also ensuring that the voltage on each phase conforms to a voltage band of 0.97-1.03 p.u.. The sequence chosen by the capacitor switching algorithm was 0000100_2 (Configuration 4) in this study case for each hour of the day.

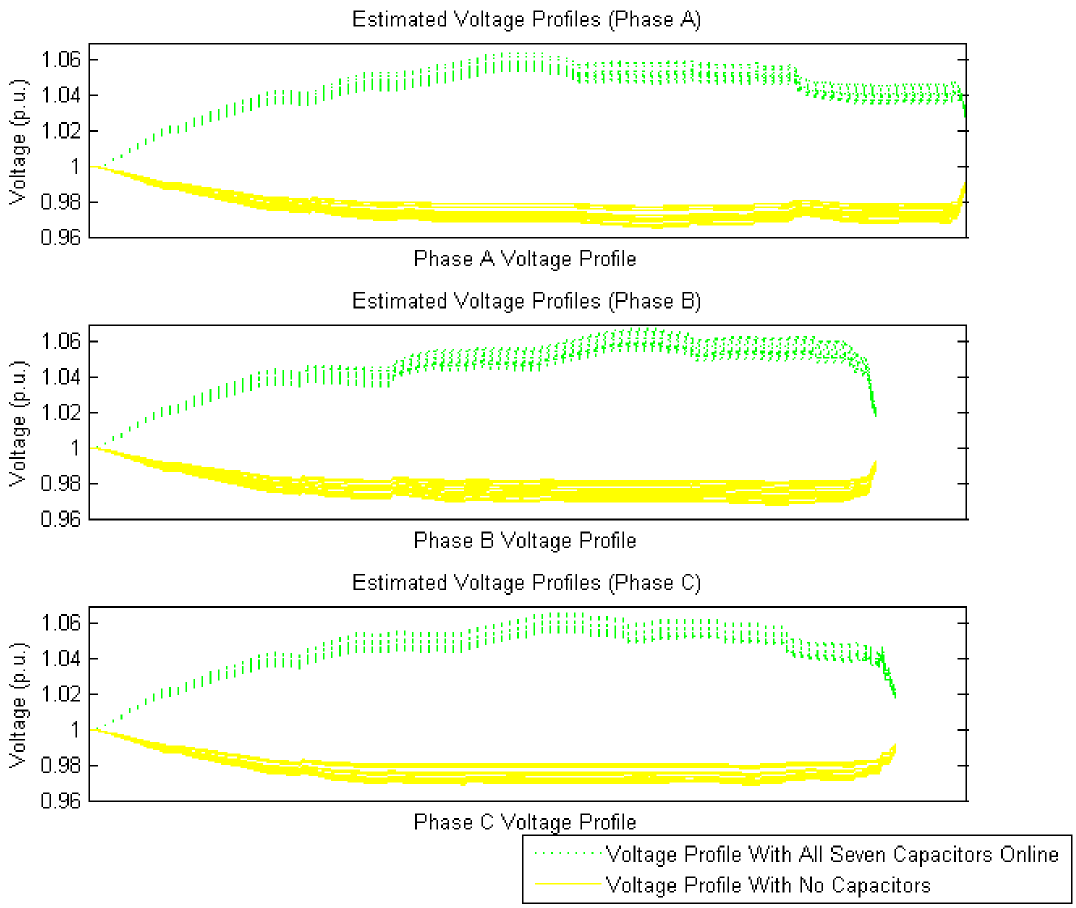

Figure 5.13: Possible Voltage Range for Each Phase, Voltage Performance.

In the study, the performance of the capacitor switching algorithm was compared to another method where the capacitors are switched online in a predetermined order with no forecasted knowledge. Essentially, the ordered sequence method monitors the total load on the feeder and turns a capacitor bank online when the load increases through the day and removes a capacitor bank when the load reduces. In this case the ordered sequence chosen was 0000001_2 (Configuration 1).

Figures 5.14 through 5.16 compare the 24 hour voltage profiles between the proposed algorithm and the predetermined ordered method for each voltage phase. The dotted curves in the figures represent the voltage profiles for each hour of the day selected by the ordered method. The continuous curves in the figures are the voltage profiles for each hour of the day selected by the dissertation's algorithm.

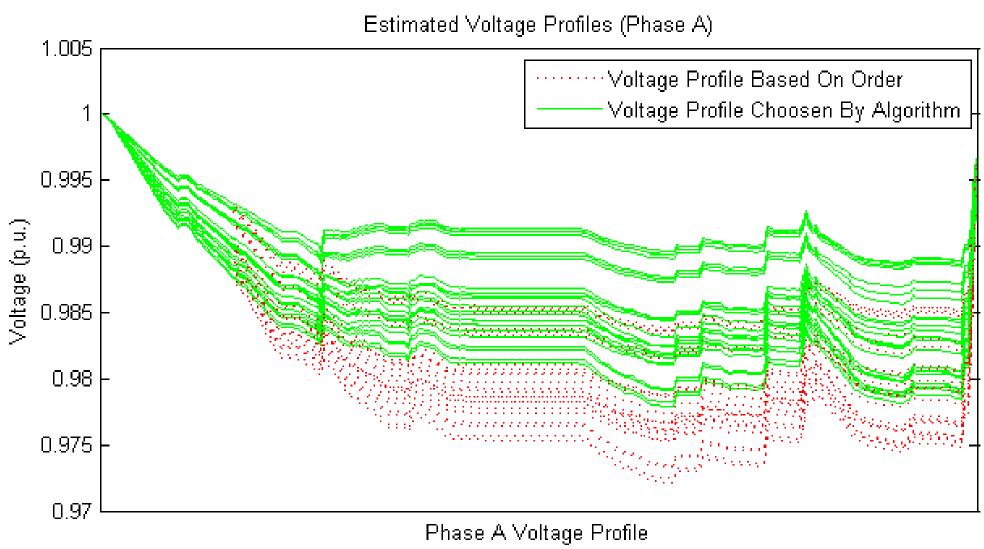

Figure 5.14: Comparison of Voltage Profile Methods, Phase A, Voltage Performance.

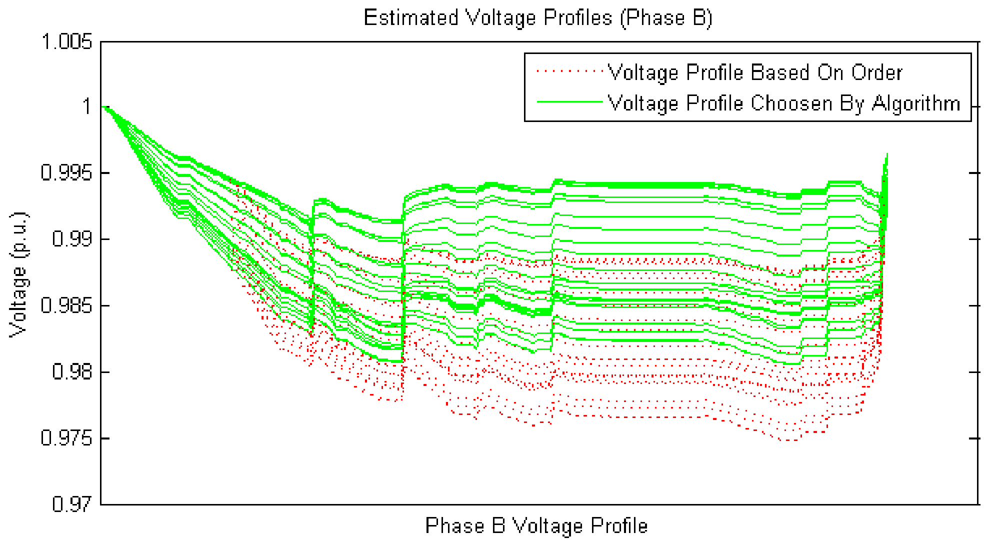

Figure 5.15: Comparison of Voltage Profile Methods, Phase B, Voltage Performance.

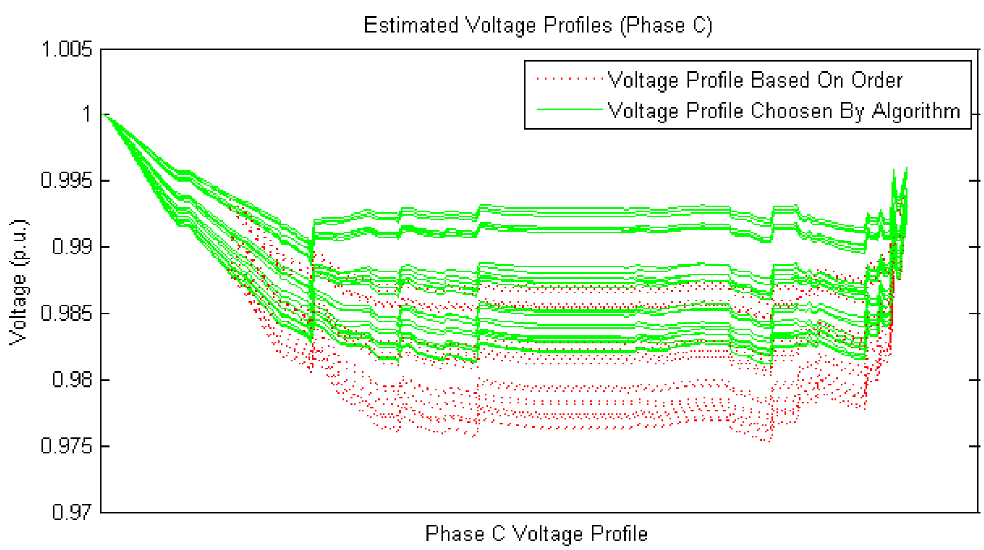

Figure 5.16: Comparison of Voltage Profile Methods, Phase C, Voltage Performance.

In this switching example, each switching sequence meets the voltage profile band requirement for each hour of the day. The predetermined ordered method has no knowledge of the future conditions on the feeder therefore it will always turn on capacitor bank one (Configuration 1) along the feeder. However, as shown in Figures 5.14 through 5.16, the third capacitor bank (Configuration 4) selected by the dissertation's algorithm is a better selection. The third capacitor bank provides a voltage profile that is closer to the nominal voltage. In order to match the performance of the dissertation's switching algorithm, the ordered method would have to switch online another capacitor bank. This example shows that the switching order of the capacitor banks makes a difference in providing the best voltage support for the feeder.

5.4.2 Capacitor Switching for Switching Reduction

For the second capacitor bank switching study, the ANNSTLF total load values were increased to simulate an extreme summer day so that the capacitor bank switching algorithm could be evaluated on days when more than one capacitor bank is needed. Figure 5.17 displays the 24 hour curves for two cases, without any capacitor banks online and with all the capacitor banks online. From the figure, the voltage profile of the case without any capacitor banks online is below the acceptable voltage band of 0.97-1.03 p.u. which means that capacitor bank reactive power support must be switched online to increase the voltage profile of the feeder.

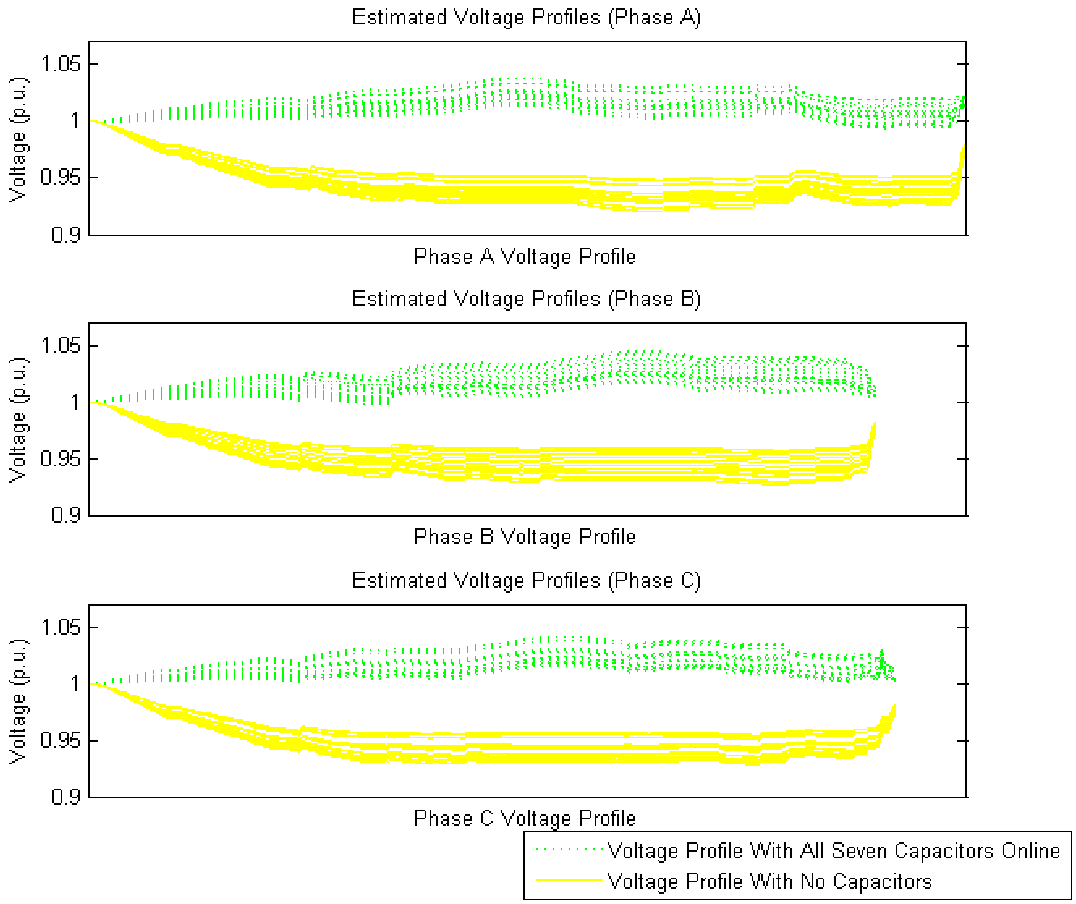

Figure 5.17: Possible Voltage Range for Each Phase, Switching Reduction.

Table 5.3 shows the ordered method and the dissertation's algorithm switching schedule for the day. The ordered method without any forecasted knowledge of the feeder voltage profile must switch capacitor banks online and offline more than the dissertation's method of computing the optimum switching schedule. Figures 5.18 through 5.20 show that both methods have similar performance on each phase where each method increased the voltage into the acceptable voltage band. While both methods produce results within the acceptable voltage band, the capacitor switching algorithm does so with less switching operations.

Table 5.3: Switching Schedule Comparison

Hour	Switching By Order	Switching By Algorithm
1	0001111_2 (15)	1011110_2 (94)
2		
3		
4		
5		
6		
7		
8	0011111_2 (31)	
9		
10		
11		
12		
13		
14	0111111_2 (63)	
15		
16		
17		
18		
19		
20	0011111_2 (31)	
21		
22		
23		
24		

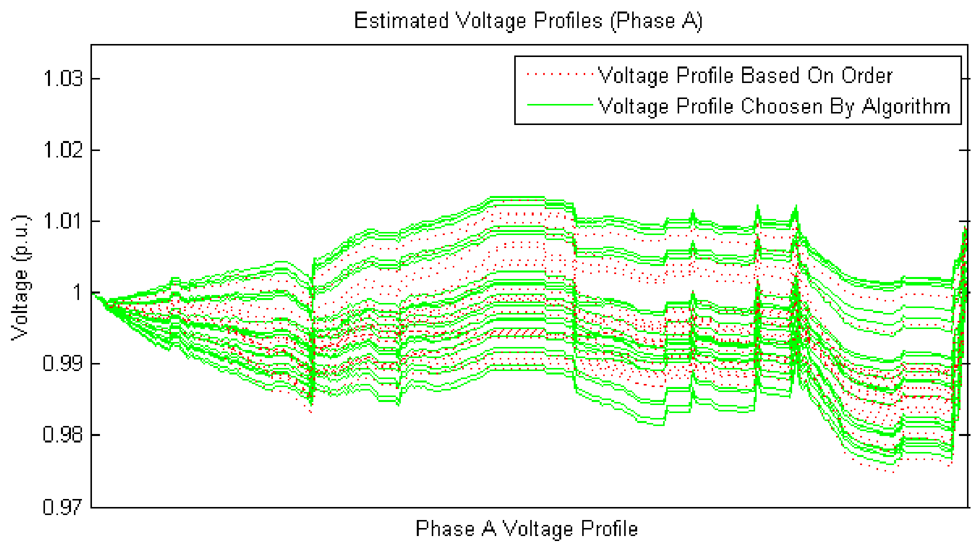

Figure 5.18: Comparison of Voltage Profile Methods, Phase A, Switching Reduction.

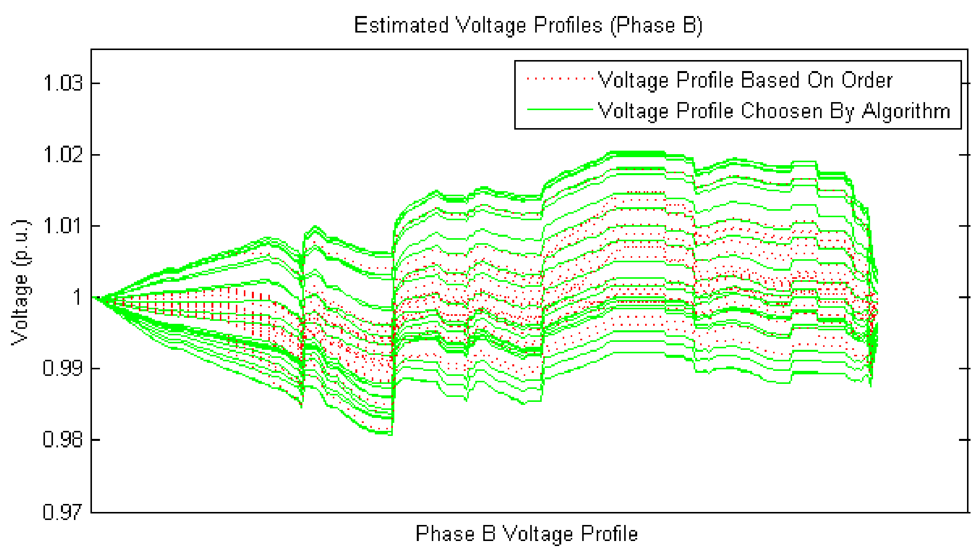

Figure 5.19: Comparison of Voltage Profile Methods, Phase B, Switching Reduction.

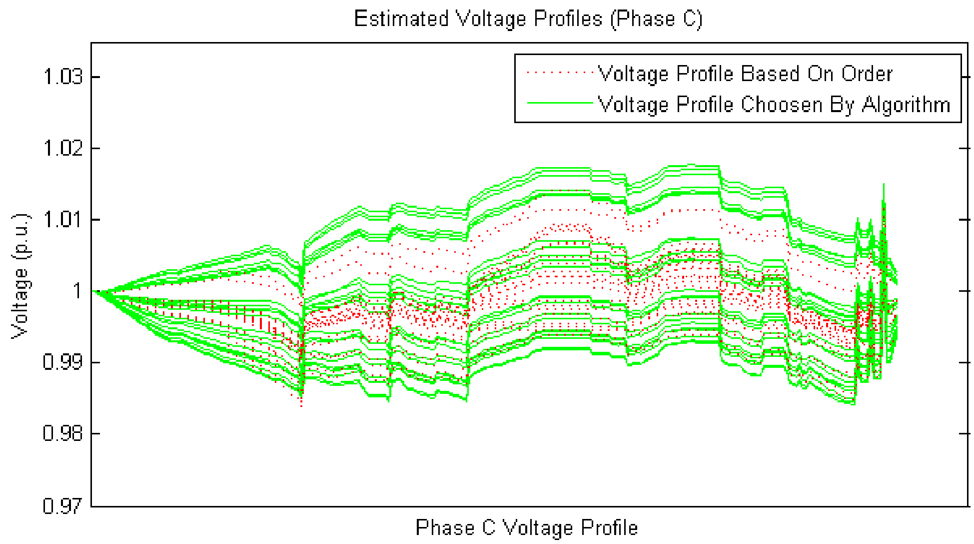

Figure 5.20: Comparison of Voltage Profile Methods, Phase C, Switching Reduction.

With forecasted knowledge of the voltage conditions, the capacitor switching algorithm can select the best capacitor bank to switch online for the desired switching objective. Other switching objectives can also be considered such as distributing switching operations over all capacitor banks in order to assign wear evenly on all the capacitor banks. The opposite objective can also be selected where a favored capacitor bank is switched online as much as possible.

If a situation occurs where there is a severe imbalance on the feeder then the optimal capacitor bank switching algorithm examines each phase to insure the voltage buses are within the acceptable voltage limits. For example, if phase B has a much lower voltage than phase A and phase C, then reactive compensation should be used to improve the voltage on phase B while care must be taken to not raise the voltage too high on the other two phases. The capacitor bank switching algorithm has the capability to evaluate the change of voltage for each phase. For a severe imbalance, better results can be found if the capacitors are controlled by individual phase. However, on feeders with only three-phase capacitor banks installed, the algorithm must respect the voltage band requirements for each phase and must attempt to balance the effects of the three-phase capacitor banks.

5.5 Chapter Conclusions

Knowledge of the load and voltage conditions on the distribution feeder is important for the comprehensive control of the distribution feeder. Optimizing distribution capacitor switching can also help electric delivery companies minimize the cost of installing and maintaining equipment on the distribution feeder and achieve better performance from the available capacitor banks. This chapter explored the results from the software described in this dissertation. A sample feeder was presented and results from each software task were investigated.

The results show that the ANNSTLF performs well in predicting the load profile for a utility supplied sample feeder. In addition, each phase of the voltage profile was calculated and plotted. As shown in Section 5.4, the capacitor switching algorithm can select the best capacitor bank that provides the closest voltage profile to the nominal voltage and also that it can provide minimal switching for the day.

CHAPTER 6

DISSERTATION CONCLUSIONS

This chapter presents the lessons learned through the research process and the overall benefits of the dissertation. In addition, the chapter contains recommendations for future research using the ideas presented in this dissertation.

6.1 Dissertation Conclusions

In the modern electric industry, electric power utilities must strive to obtain better performance from distribution lines and equipment while also reducing the installation and operating costs associated with the distribution system. More effective monitoring and control schemes can help maintain higher efficiency and quality standards while also reducing the repair and maintenance costs associated with the distribution system.

This dissertation has sought to improve the monitoring and control methods along a distribution feeder by introducing techniques to estimate the load and voltage profiles and optimize the control sequence of capacitor banks along a distribution feeder. Both the load profile forecasting software and the voltage profile estimation software use a minimum number of monitoring equipment to calculate the feeder load and voltage conditions. In addition, both the load profile forecasting and voltage profile estimation methods are designed for the unique characteristics of the distribution system.

The load forecasting method developed in this dissertation has several advantages over traditional forecasting. The ANNSTLF learns complex relationships between input data and output data and internally determines the variable relationships without predetermining an appropriate model. It incorporates weather data into the forecast for a more accurate forecast to increase the accuracy of the output. The ANN software supports nonlinearity in the network and permits the ANNSTLF to perform nonlinear tasks such as load forecasting with more accuracy than through linear methods. It can also adapt to new changes in the distribution system's environment, due to the ANN's intrinsic adaptability. Together with the load allocation method, the load profile and customer demand software can provide an excellent forecast of the load demand at the load buses.

The voltage profile estimation method developed in this dissertation has benefits as well. First, the dissertation's voltage profile estimation method can estimate the feeder voltages on distribution systems with unbalanced loads. Moreover, the single-phase, two-phase, and three-phase buses voltage buses can be estimated and plotted with this method. The voltage profile estimation method's main advantage is that it reduces capital expenditures by computing the voltage conditions on the feeder without installing monitoring equipment on every load bus.

An optimal capacitor bank switching algorithm was introduced as an example of using the load forecasting and voltage estimation methods. One benefit of the dissertation's capacitor bank switching method is that the algorithm looks at the entire voltage profile instead of a local segment of the feeder. Also, each capacitor bank can be coordinated with the other capacitor banks on the feeder and with voltage regulators. The capacitor bank switching algorithm can be used to decrease the amount of required maintenance on the distribution by minimizing the number of switching operations that occur on the feeder.

The dissertation has applied electrical engineering principles in the areas of artificial neural networks, distribution load flow, voltage control, and capacitor operations. It is believed that this dissertation can contribute a significant impact to utility distribution system operations.

6.2 Future Work

Future development based on this dissertation's research is possible. Because the software design for this project is modular, different parts of the research can be easily improved or interchanged. A few suggestions on areas where this dissertation's research can be extended are presented in this section.

First, different ANNSTLF designs can be explored to compare the performance of various ANN algorithms. Another area would be to extend the load allocation algorithm to use BPL or other communication protocols to obtain more accuracy for the load profile. The voltage profile estimation could also be expanded to work on distribution structures such as loop feeders and urban networks. Capacitor bank placement methods could also be explored using the sensitivity matrix described in Chapter 4.

The dissertation limited the application of the estimated load and voltage profiles to one area of power system analysis, namely distribution system level optimal capacitor bank switching. However, the load profile and customer demand forecasting algorithm and the voltage profile estimation algorithm can be applied toward many different areas in the power system. For example, the load forecasting and voltage profile estimation software could be used in optimal feeder reconfiguration for increased system security. Other areas could include load shedding, contingency analysis, or distributed generation system protection.

Finally, the software developed in the dissertation would benefit from a study of different types and configurations of distribution systems that are located in different regions and climates. For atypical distribution feeders, modifications to the software could be required, since unusual systems are not addressed in the generalized approach described in this dissertation. Also, it would be advantageous if the software were tested within or alongside a real-world distribution management system, in order to record long-term measurements for verification of the software results.

APPENDIX A

ABBREVIATION INDEX

Abbreviation	Term
AMI	Advanced Meter Infrastructure
ANN	Artificial Neural Network
ANNSTLF	Artificial Neural Network Short Term Load Forecaster
AR	Autoregressive
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARMAX	Autoregressive Moving Average with Exogenous Variables
ARIMAX	Autoregressive Integrated Moving Average with Exogenous Variables
BPL	Broadband over Powerline
ESRC	Energy Systems Research Center
LPCDF	Load Profile and Customer Demand Forecasting
LTC	Load Tap Changing transformers
MA	Moving-Average
MAPE	Mean Average Percent Error
MLP	Multi-layer Perceptron
PDF	Probability Density Function
PLC	Power Line Carrier
SVC	Static Var Compensators
WLS	Weighted Least Squares

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