DELIVERY POINT LOAD FORECASTING

by

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ABSTRACT

MASOUD SOBHANI. Delivery Point Load Forecasting. (Under the direction of DR. TAO HONG)

Electric load forecasting has been integrated into the business decision making processes across virtually every segment of the power industry. Power companies use short-term and long-term load forecasts primarily for power systems operations and planning, while electricity retailers use load forecasts for pricing and procurement decisions. In power delivery systems, a delivery point is a node where the electricity is delivered to the distribution network in order to supply power for a local area. Load forecasts at the delivery point level provide values for distribution system operators. Load forecasters face two major challenges when forecasting the load profiles at the delivery point level: data quality and randomness of the load. Data quality issues play a vital role in producing accurate forecasts. In the power system hierarchy, the frequency of events causing the quality issues for load data is unique and more intense at the delivery point level. In this research, a delivery point load forecasting framework is proposed, which includes different components focusing on the quality issues in both load data and weather data, such as load transfer detection; meter grouping; load anomaly detection; and weather data cleansing using multiple load zones. The framework is developed and evaluated using the data from a distribution company in the United States. Enhancements of data quality in each step are evaluated within a load forecasting process. The effectiveness of the proposed solution has been empirically confirmed through significant improvements to the forecast accuracy.

DEDICATION

I dedicate this dissertation to my father, Mojtaba Sobhani. You are the one who has always been supporting and encouraging me to succeed; a dedication to the sacrifices you made for me.

ACKNOWLEDGMENTS

Before I list the names of people to express my thanks, like a typical acknowledgment, let me first tell you a short story. Back in January 2016, in the first semester of my Master's degree at UNCC, I registered for a course that was interesting to me. I was lucky enough that I did not know anyone in that department at that time to prevent me from taking that course. We started the class with more than twenty students, mainly fresh new ones like me. The professor had an aggressive beginning in the first class by announcing a massive amount of tasks and assignments that was multiple times more than a typical graduate course. "You need to spend at least 30 hours a week for this course", the professor said. It sounded like a joke to me. Well, it was not actually.

Weeks passed one by one and students kept dropping the class due to the huge workload and serious tasks. We ended up with four students when the semester did not even reach half. We were the survivors moving forward in this brutal marathon. We finished the course with an "A" grade for all of us of course. We deserved it after that "mission impossible". The following semester, when the professor saw me on the first day of another class, he said, "Are you crazy? You are the first student who took two courses with me". Well, I was even crazier than that.

I took all courses he teaches. I then asked him to join his research team. He accepted me after I passed the hiring procedure (Yes, he gives tough tasks to the students to get qualified for his team). I did my Master's thesis under his supervision in five months, but that was not the finish line. I enrolled in the Ph.D. program with him as my advisor and after two and a half years of hard-working, now we get to the endpoint presenting this dissertation.

Dr. Tao Hong has been more than an academic advisor for me. I learned from him a lot since the very first day I met him until now, and definitely in the future. He always made me put myself out of my comfort zone to grow. When I decided to enroll in the Ph.D. program, we created a detailed study plan including all courses, research milestones, conferences, and even internships I could have. He drew the timetable on a board in the lab and I still have the picture of that plan. My resume is the evidence showing that I followed that plan word by word. This was not possible without Dr. Hong's supervision. Therefore, first and foremost I would like to thank him for his continuous guidance, insight, and patience. Tao, you have been a tremendous mentor and a great friend to me. I owe you lots of gratitude for your constant support during this difficult period of my life.

This dissertation would not have been possible without those supports from many other people. The work presented in this research has been critically assessed and approved by an outstanding committee. I would like to thank my committee members, Dr. Charlotte (Pu) Wang, Dr. Churlzu Lim, Dr. Gang Chen, and Dr. Jy Wu for their time and valuable feedback and comments. The experiments of this research would not have been done without the financial and technical supports of NCEMC. Thanks, Tom Laing and Claude Martin. I am delighted to have worked with you.

I spent most of my time in the past three years in room 2341 in the EPIC building. We were like a family in the BigDEAL lab. Shreyashi Shukla, Saurabh Sangamwar, Zehan Xu, Yike Li, and Deeksha Dharmapal, thank you all for your support and help. We had a lot of fun and I already missed you.

Lastly, I would like to thank my family for all their love and encouragement. For my dad who raised me with a love of science and supported me in all my pursuits. For my mom who had to reluctantly learn to accept my separation from her and still gave me nothing but love, day after day. For my little sister, Mahsa and her little baby, Afra. I cannot pass a single day without thinking of you. Finally, for my loving, supportive, and patient wife, Shaghayegh whose faithful support during the final stages of this Ph.D. is so appreciated. Thank you.

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CHAPTER 1: INTRODUCTION

Electricity infrastructure is a basic requirement for daily life in civilized countries. Power grids as one of the most complicated systems ever made, supply electricity to various consumers. The process of producing power in a plant and transferring it to a household or a factory requires precise and detailed planning. Electricity is a unique commodity that its consumption and production happen at the same time. On the other hand, the capacity for storing electricity is negligible in comparison to the amounts of supply and demand. Therefore, predicting the future electricity demand is crucial for a power delivery system, which makes the electric load forecasting fundamental information for power system planning and operations.

Electricity demand is a function of various factors. Geographical location, weather conditions, population, energy policies, power grid structure, classification of consumers based on the sector, and many other variables drive the electricity demand for a particular group of consumers. Hence, any combination of these factors creates a unique case for load forecasting.

Deployment of smart grid technology has provided opportunities for the power industry to enhance the capabilities of system monitoring. The modern metering infrastructure has made the data available for almost all nodes in a power delivery network. System load which is the total demand of a given service zone had been almost the only option for load forecasting before the smart grid era. The availability of the data at lower levels of aggregation has opened a door for forecasters to have a better understanding of the load profiles in order to create forecasting models that are more accurate.

Delivery points are the nodes in a power delivery network where electricity is delivered to the distribution system. The physical representatives of the delivery points are medium/low voltage substations that connect transmission lines to distribution lines. In a load aggregation hierarchy, a delivery point is located somewhere in the middle, which is higher than end-user level and lower than the system level. Therefore, the characteristics of the load profiles at the delivery point level are different from the ones at lower or higher levels. As a result, load forecasting at the delivery point level requires a distinctive solution.

In this chapter, first, we briefly introduce the structure of a power delivery system. Then, the process of a typical load forecasting is explained. The last two sections describe the problem and corresponding challenges for delivery point load forecasting.

1.1 The Structure of Power Systems

A classic power system consists of three main components including generation, transmission, and distribution. The corresponding equipment includes generators, transformers (step-up and step-down), transmission and distribution lines, cables and switchgear (Sallam & Malik, 2011). Figure 1.1 shows a schematic diagram of a power system. At the first place, generators produce electricity. To transmit the power through long distance lines in an economic way, the voltage increases in the step-up transformers. When the electricity arrives at the distribution lines, the extra high voltage (EHV) power should be stepped down to the medium voltage (MV). The power is then transmitted through transmission lines to the secondary substations. The distribution transformers reduce the voltage to the consumers' level. At the final step, the low voltage (LV) power is delivered to the end users, which can be either residential, commercial or industrial consumers.

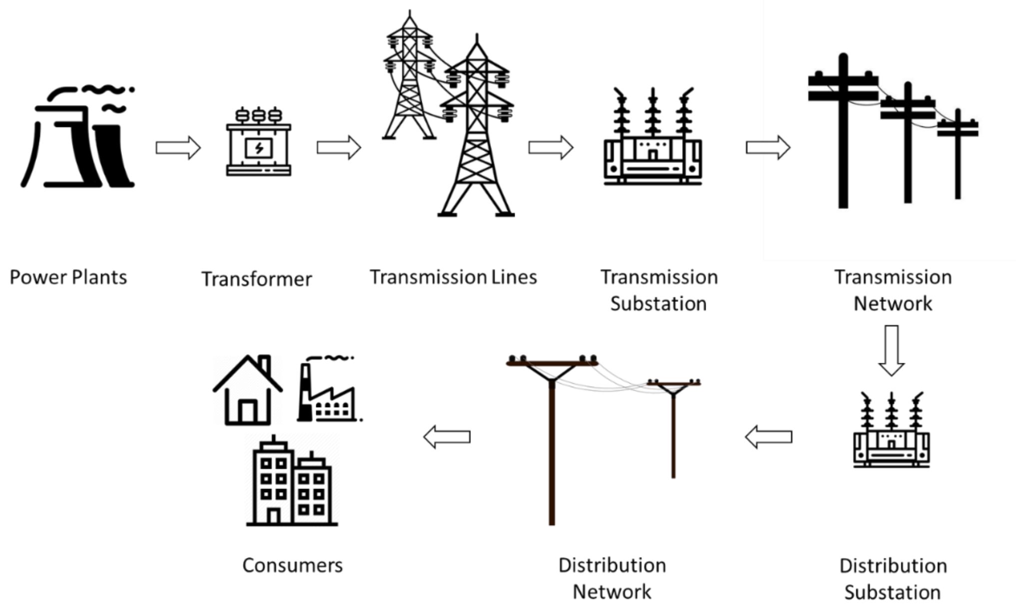

Figure 1.1: A schematic diagram of a power system

In addition to the main three components of a power system (generation, transmission, and distribution), technology improvements of the recent years have introduced another component to the classic arrangements. Previously, the traditional role of end-users in a power system was only consuming energy. Due to the deployment of smart grid technology, penetration of distributed energy resources (DER) such as solar roofs and small-sized wind turbines, and batteries an end-user is converted to an active component in a power grid. In addition, the bi-directional connection between the consumers and power utilities (because of Advanced Metering Infrastructure) makes it possible for the consumers to play a role in controlling the power system.

Utilization of the smart grid technologies in the past decades has improved the monitoring capacity of the power system. The integration of advanced metering infrastructure (AMI) to the smart grid has provided opportunities for the system operators to have near real-time data from the different points of the power network in high resolutions. The availability of the data in a massive order makes it possible to enhance the reliability of power delivery. In addition, analyzing the data at different levels of a power hierarchy requires exploring deeper, tacking new challenges and proposing novel solutions.

1.2 Electric Load Forecasting

Electric load forecasting is an essential input for decision-making in the power industry. Virtually, every sector from generation to transmission and distribution requires load forecasts for the planning and operations. The scheduling functions such as unit commitment, economic dispatch, and automatic generation control rely heavily on load forecasts (Yue, Hong, & Wang, 2019).

The term electric load forecasting refers to the process of predicting future electric demand. A typical electric load forecasting process consists of three main components; input, model and output. Depending on the problem and application, these components could be different.

The electricity consumption of a residential customer is responsive to weather variations because humans always expect comfortable ambient conditions. During the hot days in summer, we turn the A/C on to cool down the temperature and in the cold days of winter, heaters make homes warm. This significant correlation between the weather and electric consumption has been used in developing load forecasting models (Refer to section

3.1). Although temperature is one of the best explanatory variables in load forecasting models, other measurements such as humidity, cloud cover or wind speed could be employed to have better modeling.

Typically, electric load profiles have three seasonal blocks, including the month of a year, days of a week, and hours of a day. The yearly block is due to the weather variations in different seasons of a year (see section 3.1 and Figure 4.4). In a weekly block, the work schedule of people makes the load profiles of weekdays different from the ones at weekends. Human activities and weather conditions are different in 24 hours a day. Therefore, in a daily block, the electric demand is not similar in different hours. Load forecasting models capture these three seasonal blocks by employing the calendar variables. Hence, categorical variables such as the month of a year or days of a week are utilized in load forecasting models.

Depending on the application, load forecasting models use more variables other than weather and calendar variables. In long-term load forecasting, the prediction horizon is a few years ahead or longer. These forecasts are used for decision-making such as network expansion or building new power plants. In such cases, some socioeconomic variables such as population, gross domestic product (GDP) and land usage are better explanatory variables than the weather.

The forecasting models can be categorized into two main groups; statistical and artificial intelligence (AI) models. The models based on statistical techniques are more interpretable than AI models. Time series or univariate models are basic statistical methods that only use the history of the target variable (load here) to capture the patterns. The methods include but not limited to Exponential Smoothing, Autoregressive, Moving

Average, ARMA and ARIMA (Autoregressive and Moving Average), ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH (Generalized ARCH). Univariate models are useful when only endogenous variables are adequate to model the dependent variable. In addition, for longer forecasting horizon (more than a few steps ahead) time series models are not reliable and result in inaccurate forecasts. On the other hand, when exogenous variables have a considerable impact on the variation of the dependent variable, more advanced statistical models come into play. Multiple Linear Regression (MLR) is a well-known technique for developing forecasting models.

The correlation between the load and exogenous variables are usually nonlinear. Although statistical methods are able to model nonlinearities in the data, AI models have better performance in capturing complex correlations in some cases. Models such as Artificial Neural Network (ANN), machine learning or gradient boosting are some AI methods that have been used to develop load forecasting models. These models are called black box because the process inside these models is very complicated and hard to be interpreted.

In the power industry, point load forecasting has been a classic and favorite approach for a long time. In point load forecasting, the output is a single value for every timestamp in the future. In the past decades, due to the deployment of smart grids and the penetration of renewable resources, the need for predicting the future uncertainty is getting more challenging. Therefore, probabilistic load forecasting emerged as a solution to the modern challenges in the power industry, because it can provide more information about future uncertainties than what point forecasts can do (Y. Wang, Zhang, et al., 2018). Probabilistic forecasting provides a range of outputs for each timestamp in the future.

Hence, varieties of future outcomes are available for the decision-makers in the power industry. The probability of the future load gives the power utilities a handful of options for planning and operations.

Traditionally, system load has been the preferred load level to analyze the power supply system. In the past decades, the integration of smart meters into the power grid provided the power industry with new opportunities by utilizing load hierarchies in order to improve the system performance. Load forecasts at different levels of hierarchy, from the system level to the end-users' have different applications. The electric utilities use short-term and long-term load forecasts at the system level to plan their operations while the electricity retailers use load forecasts at the end-user level for pricing and procurement decisions. In addition, availability of the data with high granularity, either temporally or spatially, provides extensive chances to better understand electric load profiles and to improve the load forecasts.

Developing and implementing load forecasting solutions are subjective to the conditions and constraints. Variable and model selection, weather station selection and combination, data cleansing, determining the length of history and residual analysis are a few examples for the procedures that a load forecasting process requires to be developed. In the following section, we review some fundamental concerns in a load forecasting process focusing on the delivery point level.

1.3 Randomness and Data Quality

Two factors play a vital role in the success of a load forecasting process: randomness and data quality. Accurate outputs of a forecasting process are results of inputting high-quality data into a strong model (randomness).

Although there is no certain definition for randomness, the interpretations of randomness could be summarized to three terms: unpredictability, typicality, and complexity. However, Khrennikov (2014) believes that none of the three basic mathematical approaches led to a consistent theory of randomness. The author concludes to the idea that randomness is not a mathematical but physical notion. Nevertheless, the definition of randomness in this research follows the idea of (Khrennikov, 2014), as well as three interpretations.

To be more concise in electric load forecasting, the randomness mainly refers to unpredictability. High randomness is due to the difficulties in forecasting. Assume that we have a collection of load profiles from different households in a neighborhood. If we use a given model to forecast the load profile of each household, the predictions are likely to be very different. Randomness is the major factor in this case for variations of the accuracies. The model may work for a certain number of households but not for all of them. This is due to what Khrennikov (2014) mentioned that randomness is a physical notion.

The electricity consumption of a given household is impacted by two driving factors, weather condition, and human activities. In a neighborhood, the weather condition is similar for all households, but human activities are different. The number of people, the number of adults and children, work schedule and many other human-related factors have considerable impacts on electricity consumption. This is the origin of randomness in electric load profiles.

Data quality is another important player in a load forecasting process. Generally, in any process, the quality of output is determined by the quality of input. In computer science and mathematics, garbage in garbage out (GIGO) is a common concept indicating the importance of input quality. It means that a high-quality output should not be expected by a low-quality input in a process.

In load forecasting, as mentioned earlier in this chapter, we have different types of input data. Load and weather data are two major input variables. The quality of input data is crucial to forecast accuracy. On the other hand, real-world data always contain outliers and inconsistencies. Human error, instrument failures, natural events, and many other reasons create anomalies in the data. Therefore, in order to have accurate predictions, we should take care of anomalies and data quality issues in the input data. A healthy forecasting process should have an anomaly screening at the early stages to be able to produce accurate predictions.

Load profiles at each level of a load hierarchy have different features and shapes. Forecasting the load at a given level requires particular analysis, modeling, and solution. Figure 1.2 displays a diagram of a load hierarchy in a power grid. This graph has four levels of aggregation: system, load zones, delivery points, and households. A hierarchy could have more or fewer levels but the concept is the same. As we move towards the lower levels of the system, the randomness of the load profiles increases and the data quality decreases.

High randomness means that there are fewer patterns to capture in the load profiles. This concept is tied to the level of predictability. The load profiles of the lowest level (household) represent the consumption behaviors of different end-users. Therefore, more random load profiles must be expected at this level due to the arbitrary nature of human behaviors. Aggregating the profiles of a number of households smooths the shapes and as we move to a higher level of aggregation, the load patterns get more repetitive and hence become more predictable. Hence, the profiles of the higher levels are respectively easier to model because of the predictable patterns they have.

On the other hand, at lower levels of the hierarchy, the data quality issues are more frequent and more diverse. For example, the reading failures of a smart meter are reflected in the corresponding household load profile, but the aggregating of multiple profiles wipes out the missing values.

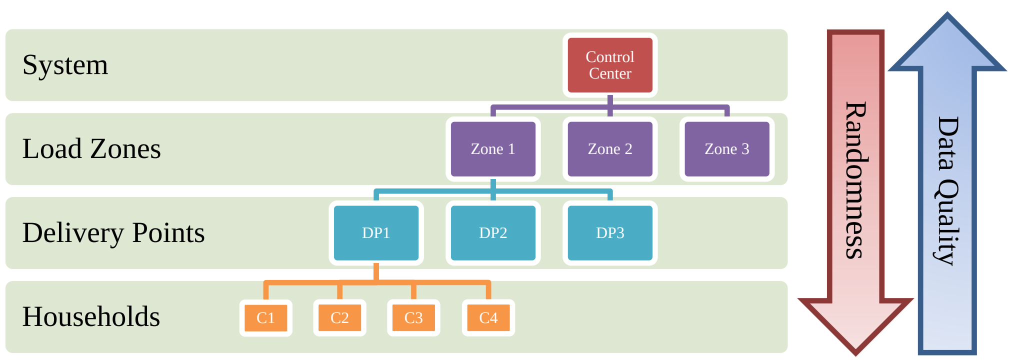

Figure 1.2: Load hierarchy in a power grid

High randomness and intense data quality issues make the forecasting challenging at lower levels of the hierarchy. In this research, the main focus is in data quality issues and their impacts on the accuracy of load forecasting at the delivery point level.

Randomness, which could be controlled by customized forecasting models, is not the scope of this research. Therefore, in the proposed solution for delivery point forecasting, one particular model is used to keep the experiments consistent. Having a similar model for all experiments, the impacts of data quality issues can be investigated distinctively.

1.4 Delivery Point Load Forecasting

Deployment of smart grid technology has provided the opportunity for the power industry to have access to a vast amount of data. Before the smart grid era, the system load forecast was a typical input for power system planning and operations. The availability of the data from the highest to the lowest levels of a load hierarchy opens new doors for all participants of the power industry to improve the system reliability. As a result, the load forecast of the lower levels has provided more information for the decision-makers in the power industry.

In a power delivery system, delivery points are the substations that deliver electricity from transmission lines to the distribution network. These substations supply power for a limited area such as a couple of neighborhoods or a building block. For example, the power demand of a given county is supplied typically through a few delivery points. The meter located in a substation monitors the electricity flow of the corresponding service zone.

Analysis of the load data from the meters located at delivery points provides valuable information, which is useful for different applications. In a large service territory, the driving factors of energy consumption are not similar for all consumers. Therefore, the load profiles are expected to have different patterns and shapes depending on factors such as demographics, weather conditions, and the sector. More accurate load forecasts at lower levels of a system create values for the power system planning and operations. The forecast at this level can leverage the accuracy of predictions at the upper levels of the system because it is customized for the conditions of the corresponding service zone. In addition, the predictions of the electricity flow through a given substation help the distribution operators have better planning to avoid outages due to the overloading of equipment. Eventually, the load forecast at lower levels gives the strength to the system operators to use the capacity of a smart grid in order to improve the system reliability.

Delivery point load forecasting means predicting the load demand of a service zone supplied through a given delivery point. As we discussed in the previous section, the patterns of the load profiles at different levels of a power system hierarchy are not similar. Delivery points belong to MV/LV levels of the power system. Randomness and data quality issues are two major factors that play vital roles in the development of a forecasting framework for load time series of the delivery points. Although a strong forecasting model may capture nonlinear and irregular patterns of the load profile at a delivery point, the intensive data quality issues at this level affect the performance of the forecasting models significantly.

The quality of input is crucial to the quality of output in any process. The same analogy can be adapted for electric load forecasting. The quality of the input data in a load forecasting process is vital for forecast accuracies. The hypothesis of this research relies on this concept that improving the data quality in a delivery point load forecasting enhances the accuracy of outcomes. In this hypothesis, we should quantify the “quality” factors to be able to evaluate it in order to test the hypothesis. The quality of output is measured through the accuracy of load forecasts. The forecasted values are compared to the actual values through some metrics to calculate the accuracy. The quality of input data is quantified through detecting anomalies in the data. An anomaly is defined by comparing it to a normal observation. In this research, we will define the anomalies in delivery point load data, as well as the ones in temperature time series. Therefore, by quantifying the quality of input and output in the delivery point load forecasting we will test the hypothesis.

Load transfers and outages are two major sources of data quality issues in the load profiles of delivery points. Load transfer is a load management task to improve system reliability. Distribution operators transfer the load from one substation to another one due to some reasons such as maintenance and congestion. An outage is typically due to some natural causes or equipment failures. Outages usually occur in local areas and depending on the intensity of the outage, the load profiles of one or more substations could be impacted. Both load transfers and outages are common events that cause noticeable effects on the load profiles. In addition, other factors such as meter failure, human error in recording or reporting can create some anomalies in the load profile and any level including delivery points.

Data quality issues are not limited only to load data. Weather data which is a fundamental input in many load forecasting models have also anomalies and inconsistencies. Similarly, since we use weather variables in delivery point load forecasting models, we need to check the quality of weather data in the forecasting process.

The intensity of the data quality issues along with the higher level of randomness makes the load profiles at the delivery point level unique. Therefore, forecasting the load at this low/medium voltage level requires a distinct solution. In this research, we conduct a comprehensive study on the challenges at delivery point load forecasting. Our focus is mainly on data quality issues. In this research, we propose a framework to tackle these problems. The framework consists of a few components and each component addresses a specific challenge for delivery point load forecasting. The challenges are identified first and then fixed by a proposed solution. The proposed framework is evaluated through a case study using the data from a power utility in the United States.

1.5 Dissertation Organization

The organization of the dissertation is shown in Figure 1.3. Chapter two presents a literature review on electric load forecasting, load forecasting at MV/LV level and data quality issues. Chapter 3 gives a brief background from the statistical tools we use in this research. Chapter 4 introduces the data used in this research and presents a brief analysis of the data. Chapter 5 proposes a comprehensive methodology for detecting load transfers, as well as experiments and discussions on the results. Chapter 6 propose a solution for improving the data quality in meters with load transfers. In chapter 7, other data quality issues in delivery point load profiles are studied. Chapter 8 propose a methodology for weather data cleansing. Chapter 9 summarizes different components in order to propose a framework for the delivery point load forecasting. The research concludes in chapter 10.

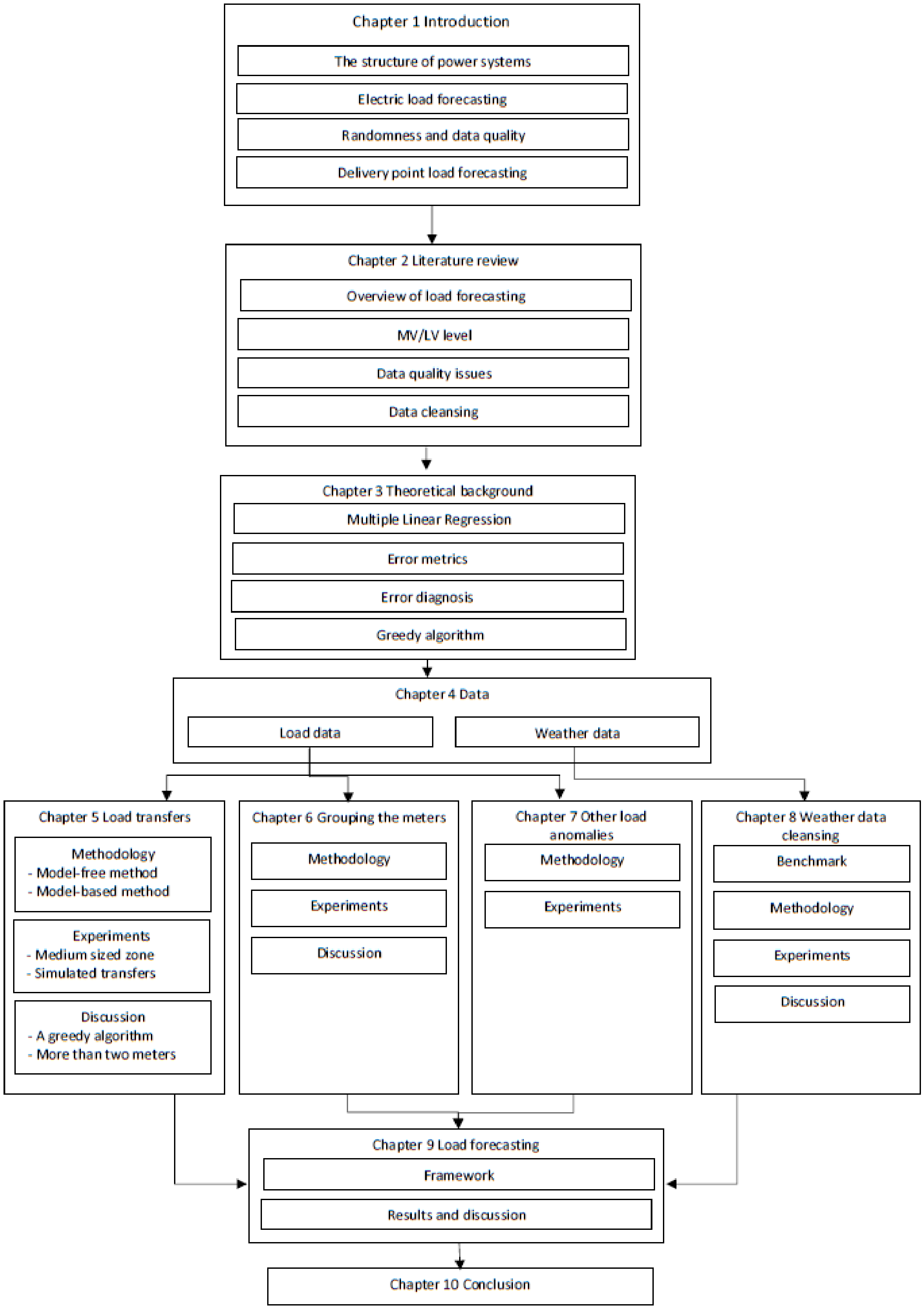

Figure 1.3: The organization of the dissertation

CHAPTER 2: LITERATURE REVIEW

2.1 Overview of Load Forecasting

Electric Load forecasting owns a wealthy literature with a sharp increase in publications in the past decades (Hong & Fan, 2016). Figure 2.1 shows the number of journal papers published in the field of electric load forecasting and related subjects since 1985 (Web of Science query, TS = (load forecasting OR (electricity consumption AND forecasting) OR electric load forecasting OR energy forecasting))). The significant raise in the publications within the past decades is an evidence to the importance of load forecasting and the demand for new solutions. In this section, we review different angles of the literature and the representative papers to provide a perspective for the challenges and solutions in electric load forecasting.

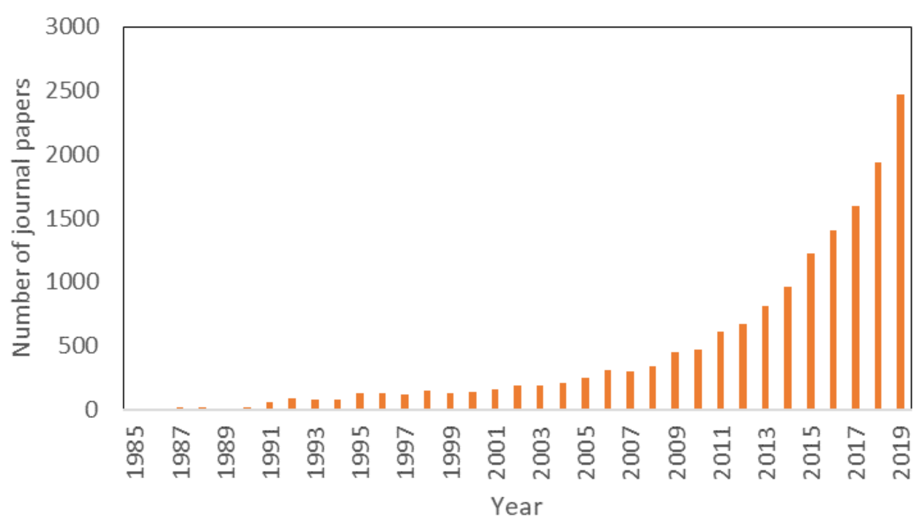

Figure 2.1: Number of journal papers in Web of Science (WoS) for the field of electric load forecasting

Model is a required and important component in a load forecasting process. A major portion of papers in the literature focused on proposing accurate and effective forecasting models. Various techniques and methods have been used in developing load forecasting models such as statistical and artificial intelligence techniques. Table 2.1 shows some forecasting models that have been used frequently in the literature and some representative papers in this field.

Table 2.1: The list of frequently used forecasting models and some representative papers

Model	***Papers***
Exponential Smoothing	(Hyndman, 2008), (Taylor, 2008)
ARIMA	(Amjady, 2001), (Huang & Shih, 2003)
MLR	(Papalexopoulos & Hesterberg, 1990), (Hong, Pinson, & Fan, 2014), (P. Wang, Liu, & Hong, 2016)
ANN	(Khotanzad, Afkhami-Rohani, & Maratukulam, 1998), (Hippert, Pedreira, & Souza, 2001)
Semi Parametric	(Fan & Hyndman, 2012), (Nedellec, Cugliari, & Goude, 2014)
Fuzzy Regression	(Hong & Wang, 2014)
SVR	(B.-J. Chen, Chang, & Lin, 2004)
Gradient Boosting	(Ben-Taieb & Hyndman, 2014)

Traditionally, time series models have been the favorite techniques in forecasting problems. Univariate models such as Exponential Smoothing (Hyndman, 2008) and ARIMA (Autoregressive Integrated Moving Average) use the history of the target variable (load here) to predict the next values. ARIMA is used as a model for short-term load forecasting in (Amjady, 2001). Different customized models were developed for weekdays, weekends and public holidays. The proposed model also showed capabilities for peak load forecasting. A modified version of the ARIMA model was proposed in (Huang & Shih, 2003) for short-term load forecasting by integrating Non-Gaussian process. The model was tested in a case study for a day-ahead, week-ahead, and peak load forecasting. A few time series models including ARIMA and variations of Holt-Winter’s exponential smoothing model were evaluated in (Taylor, 2008) for very short term load forecasting.

Time series models are typically good models when the forecasting horizon is just a few steps ahead. The longer horizons, the accuracy of univariate models drops dramatically. In addition, load history is not the only variable to capture the features of a load profile. Other factors could also have effects on energy consumption. Although time series models could show reasonable performance in forecasting, the univariate nature of them ignores the effects of other driving factors.

Regression is a powerful statistical tool to explain the variations of a dependent variable using explanatory variables. Hong (2010) proposed a Multiple Linear Regression (MLR) model for short term electric load forecasting. The forecasting model utilizes the correlation between temperature and load of residential consumers to capture the features of the load profiles. The proposed model has been used as the benchmark in many competitions and researches (Hong, Pinson, et al., 2014). The model was improved later in another research by exploring different numbers of lagged temperature variables to study the recency effects in electricity consumption (P. Wang et al., 2016).

Artificial Intelligence (AI) and specifically neural network models have been favorite techniques for forecasters in the past and today. In electric load forecasting, neural network models were dominant for years in the late twentieth century and years after (Khotanzad et al., 1998). A review of neural network models for short-term load forecasting is presented in (Hippert et al., 2001) and the representative models are evaluated and compared in a case study. A neural network model is used in (Taylor & Buizza, 2002) to predict the load for one to ten days ahead.

Other methods and techniques were also used in developing load forecasting models such as fuzzy regression models (Hong & Wang, 2014), support vector regression (SVR) models (B.-J. Chen et al., 2004), semi-parametric models (Fan & Hyndman, 2012)(Nedellec et al., 2014) and gradient boosting models (Ben-Taieb & Hyndman, 2014).

Load forecasting models employ a variety of variables to capture salient features of load profiles. Weather is a major driving factor for residential electricity consumption. Temperature is an explanatory variable that has been used frequently in load forecasting models. Hong (2010) employed a third-order polynomial function to model the u-shaped scatter plot of load versus temperature. The variation of weather conditions in a large geographical area increases the diversity of the load profiles. A multiregional load forecasting is proposed in (Fan, Methaprayoon, & Lee, 2009) for the system load with a large service zone. Nedellec et al. (2014) employed an exponential smoothing of real temperature in a semi-parametric approach for short and medium-term load forecasting .

The researchers have used the weather variables other than the temperature in load forecasting models. The impacts of different weather variables on monthly electric demand are studied in (Hor, Watson, & Majithia, 2005). Wind speed is used as Wind Chill Index (WCI) in (Xie & Hong, 2017) for a load forecasting practice and a similar study was conducted on including relative humidity in a load forecasting model in (Xie, Chen, Hong, & Laing, 2018).

Weather stations record the weather conditions for a limited area using point measurements of the instruments. On the other hand, consumers are typically distributed across a larger area. Therefore, a single weather station is not always adequate to represent the weather condition of a large service zone. Hong, Wang, and White (2015) proposed a novel methodology for selection and combination of multiple weather stations for load forecasting (Hong et al., 2015). For a combination of weather stations in load forecasting, different methods were tested in (Sobhani et al., 2019) such as linear weights, geometrical average and genetic algorithm. The proposed combination methods were compared to the simple average as the benchmark in order to find the appropriate combination method.

In most load forecasting models, calendar variables are used to explain the seasonal behavior and time-dependent features of the load data. The seasonal blocks are modeled in many load forecasting models by employing the month of a year, day of a week and hour of a day as the explanatory variables (Hong, 2010). To model the yearly seasonal block, 24 solar-term variables are used in (Xie & Hong, 2018a). The load profiles are different on holidays. Some papers proposed solutions to consider holiday effects in load forecasting (Song, Baek, Hong, & Jang, 2005)(Ziel, 2018).

In the competition between point load forecasting vs. probabilistic load forecasting, the former wins in terms of the number of publications. However, in the past decade, probabilistic load forecasting has attracted more attention from the researchers. A tutorial review on the literature of probabilistic load forecasting is presented in (Hong & Fan, 2016). A probabilistic load forecasting can be achieved through three main approaches: simulating input scenarios representing the future uncertainties (Hyndman & Fan, 2010)(Xie & Hong, 2018b)(Bracale, Caramia, De Falco, & Hong, 2020), using probabilistic models such as quantile regression (Ben-Taieb, Huser, Hyndman, & Genton, 2016), and output simulation such as forecast combination (Liu, Nowotarski, Hong, & Weron, 2017) or simulating residuals (Xie, Hong, Laing, & Kang, 2017).

The majority of the literature is devoted to the research on the weather-responsive load while industrial load forecasting has attracted less attention. Some papers proposed methodologies for load forecasting in a factory (Bracale, Carpinelli, De Falco, & Hong, 2017)(Ahmad, Javaid, Guizani, Alrajeh, & Khan, 2017) or for load consumption of industrial appliances (Alasali, Haben, Becerra, & Holderbaum, 2018). Reactive power forecasting has been touched rarely in the literature (Bracale, Carpinelli, De Falco, & Hong, 2019).

With respect to the forecast horizon, we can categorize load forecasting to the short-term, medium-term and long-term. The cut-offs for these three categories are two weeks and three years respectively (Hong & Fan, 2016). Most of the papers we have reviewed in this section so far are on short-term forecasting. A solution to long-term peak load forecasting is proposed in (Hyndman & Fan, 2010). A long-term probabilistic forecasting methodology is presented in (Hong, Wilson, & Xie, 2014) and the benefits of using higher resolution data are compared with low-resolution ones. On the other hand, the methodology proposed in (Kandil, El-Debeiky, & Hasanien, 2002) used low-resolution data to predict the demand for fast-developing utilities.

Traditionally, load forecasting at the system level was dominant approach in both academia and the industry. Deployment of smart meters has provided the opportunities for the power industry to study load profiles of other levels, from households to larger load zones (Ben-Taieb, Taylor, & Hyndman, 2017). Global Energy Forecasting Competition 2014 and 2017 presented the most significant developments in Hierarchical Load Forecasting (HLF) and Probabilistic HLF respectively (Hong, Pinson, et al., 2014)(Hong, Xie, & Black, 2019). Hierarchical load forecasting is a vast topic to cover the challenges in different levels of the load hierarchy. Forecasting the load of the households is becoming necessary for the power utility to provide better services for their clients. A comprehensive review on topics, challenges and current solutions for the smart meter era is presented in (Y. Wang, Chen, Hong, & Kang, 2018).

Data integrity and cyber security are another emerging fields of study in the power industry. Robust and cyber-secure load forecasting models (Yue et al., 2019)(Luo, Hong, & Fang, 2018a)(Luo, Hong, & Fang, 2018b) and real-time anomaly detection methods (Luo, Hong, & Yue, 2018) were proposed in the literature to address the new challenges of the power industry.

2.2 MV/LV Level

A small share of the literature focused on the load forecasting at levels other than system load. Recently, this field has attracted more attentions from the researchers. Global Energy Forecasting Competition 2017 addressed the challenges in load forecasting at MV/LV level (Hong et al., 2019). In this section, we review some notable papers in load forecasting at lower levels of the power hierarchy including load forecasting of bus, feeder, substation, and distribution load profiles.

A hybrid model is proposed in (Amjady, 2007) for bus load forecasting. The data of three buses as the representative load profiles are used to test the proposed model. A load forecasting framework is proposed in (Haben, Giasemidis, Ziel, & Arora, 2018) for the LV level. A dataset including 100 feeders of a small city in the UK is used to test the proposed models. Feeders provide electricity for an average of 45 households. Kernel density estimation, a simple linear regression, autoregressive, and Holt-Winters-Taylor smoothing method are compared with some naïve models to study their performances on a few-days ahead forecasting practice. In the models that include temperature variables, both ex-post and ex-ante forecasting were implemented. The paper concludes that the accuracy of the forecast is related to the feeder's size and forecasting horizon. In addition, the authors claimed that the temperature has little or no effect on the forecast accuracy. However, the conclusion is based on a case study using a dataset with only three winter months in a cold location.

Neural network models are used for substation load forecasting in some papers. A simple ANN model is used in (C. S. Chen, Tzeng, & Hwang, 1996) to forecast the loads at three substations. The accuracy of the forecast is enhanced by considering the effect of temperature variations on the load profiles. Similarly, a neural network-based model is used in (Ding, Benoit, Foggia, Besanger, & Wurtz, 2016) for the substation load forecasting. The load profile is decomposed in this paper into the normal average and the intraday variation load profiles. The missing data due to the maintenance of the transformers are replaced by the data from a similar day.

A forecasting methodology is presented in (Bennett, Stewart, & Lu, 2014) for the transformer load in Australia by using the end-user load profiles. The framework consists of an NN-based clustering method and an ARIMAX forecasting model. The data is preprocessed by removing the profiles with more than 10 missing points.

The load profiles of some MV/LV substations were analyzed by a time series model to propose a solution for day-ahead forecasting. The methodology decomposes the times series into three components; trend, season, random error. Each component is then estimated separately. The proposed methodology was evaluated by using the data from seven representative substations in France (Haben et al., 2018). A similar concept was used in (Ding, Bésanger, & Wurtz, 2015) by decomposing the load profile into the same three categories.

Some other studies focused on data at the household level (Ben-Taieb et al., 2016). Wang *et. al.* propose a review study on the literature of smart meter analytics (Y. Wang, Chen, et al., 2018). A comprehensive methodology for a hierarchical load forecasting is proposed in (Ben Taieb, Taylor, & Hyndman, 2017) using data of more than 1500 smart meters in the UK. The methodology ensures the coherency of the mean forecasts in the bottom-level time series of a hierarchy, as well as in the probabilistic forecasts. Some studies showed that more advanced methods such as neural network and sparse coding can outperform classical times series models such as ARIMA or Exponential Smoothing in forecasting of the household loads (Wu, 2007)(Yu, Mirowski, & Ho, 2017)

Wang et al. (2016) showed that the best forecasting model for the system level does not necessarily perform well in disaggregated load zones and it needs to be customized for each zone. The same result is approved in (Hayes, Gruber, & Prodanovic, 2015) by showing that a given model could produce significantly inaccurate forecasts at low voltage feeder and end-user levels in comparison to high/medium voltage substations.

The reviewed papers revealed the fact that the literature suffers from a lack of comprehensive study on load forecasting at the delivery/distribution point. Although this limited literature shed lights to some dark corners of this topic, concise and detailed research are missing due to the reasons such as the inadequacy of available data, the dominance of system-level point of view in modeling, and misleading assumptions.

2.3 Data Quality Issues

Real-world data always contain abnormal observations, which are called in different names but have similar properties. Outliers, anomalies, and inconsistencies are some terms used for abnormal observations. Grubbs defines an “outlying observation” as one that appears to deviate markedly from other members of the sample in which it occurs (Grubbs, 1969). Outlier detection and data cleansing are crucial for data analysis. The applications of outlier detection range from financial fraud detection (Ngai, Hu, Wong, Chen, & Sun, 2011) to fault detection in manufacturing and many other cases.

Data outlier detection has a history in statistics back to centuries ago (Edgeworth, 1887). Many methods and techniques have been developed for anomaly detection and data cleansing in different fields of application. Hodge and Austin introduced a survey of more recent techniques for outlier detection and their pros and cons (Hodge & Austin, 2004). The approaches to the problem of outlier detection are grouped in this paper into three categories including detecting the outliers with no prior knowledge of data, classifying the data into normal and abnormal data by modeling (supervised classification), and modeling only the normality or only abnormality.

Chandola, Banerjee, and Kumar (2009) presented a survey on anomaly detection methods in different applications. They believe that the desired anomalies are different in detection methods. They categorize the anomalies into three groups: point anomalies, which are individual data instances, contextual anomalies, and collective anomalies. The techniques are classified in this paper into three main categories: classification based (such as neural network, Bayesian network, support vector machine, and rule-based), and nearest-neighbor based (such as k-nearest neighbor, using relative density), and clustering-based methods.

Anomalies are defined by comparing to normality. Sometimes, the number of anomalies is not sufficient to be described or be modeled. Novelty detection is a solution in such cases where the data contain a majority of observations with normal conditions. A review of novelty detection research is proposed in (Pimentel, Clifton, Clifton, & Tarassenko, 2014). The novelty detection methods are grouped into probabilistic, distance-based, reconstruction-based, domain-based, and information-theoretic techniques.

A review of techniques for outlier detection of temporal data is proposed in (Gupta, Gao, Aggarwal, & Han, 2014). The paper categorizes the data type into five groups including time series data, data streams, distributed data, spatio-temporal data, and network data. For each category, the techniques and methods proposed in the literature are reviewed.

Outliers and data quality issues have an undeniable impact on model estimation. A procedure for outlier detection and model adjustments for time series data is proposed in (C. Chen & Liu, 1993a). The outliers are divided into four categories in this paper including innovational outliers (10), additive outliers (AO), level shifts (LS), and temporary change (TC). A joint outlier detection and model estimation in a repetitive procedure is proposed to address the data quality issues in time series models. The procedure is then examined in a case study by demonstrating a good performance. In another study, the authors investigated a time series forecasting when the outliers occur near or at the forecast origin (C. Chen & Liu, 1993b). The results depict that the effects of outliers become smaller as an outlier occurs further away from the forecast origin.

In linear models, earlier studies proposed some solution to tackle outliers and anomalies in regression data. Rousseeuw (1984) proposed the least median square (LMS) which is based on minimizing a more robust scale estimate than the sum of squared residuals. The proposed LMS was later found out to be inefficient. An alternative approach was proposed in (Rousseeuw & Leroy, 1987) to improve the inefficiency of the LMS algorithm. They used LMS to flag outliers in the data and then ordinary least square (OLS) is used for the model estimation.

Although robust regression methods were effective at first for the data with outliers, they were computationally intensive at the time. Detecting outliers first, removing and replacing them from the data to make them clean was an emerging solution for the data quality issues. Two procedures were proposed in (Hadi & Simonoff, 1993). In both methods, the data are separated into clean data and the points with potential outliers. A clean subset of data is determined first using two model-based algorithms. Then the extremeness of potential outliers is ranked by comparing to the clean data. In (Pena & Yohai, 1999), OLS is used to calculate the residuals and the observations with large residuals are removed from the data in order to make them clean.

A nonconvex penalized regression approach is proposed in (She & Owen, 2011) for outlier detection. To detect the outliers a mean shift parameter is added to each data point. Then by using the studentized residual, a t-test determines whether an observation is an outlier or not. The proposed solution outperforms other state-of-the-art procedures and works faster and more efficiently.

Smearing and masking are two major problems in outlier detection. Smearing means an outlier makes a normal point appears as an anomaly. Masking means an outlier prevents another one to be detected. A methodology based on Genetic Algorithm is presented in (Tolvi, 2004) to address these challenges. A dummy variable for each observation is added to the regression model indicating the possibility of being an outlier. The best model is selected in a genetic algorithm process by minimizing BIC (Bayesian information criteria) of the model. The results of the case study using two sets of data demonstrated that the GA is able to avoid the potential problems of smearing and masking.

The papers introduced in this section are some representative methods used in statistics for outlier detection and data cleansing. In this research, we leverage some of these methods to develop the proposed solution.

2.4 Data Cleansing

A few papers in the load forecasting literature addressed the data quality issues in a load forecasting process. Some papers studied the data quality issues for the load at the higher levels of the system. The winning teams of GEFCom 2012 and 2014 detected anomalies in load data to improve the accuracy of their forecasts. A winning team in the hierarchical load forecasting track of GEFCom2012 screened outliers by taking the mean hourly load as the normal value and removed the hourly loads that are less than 20% of the mean (Charlton & Singleton, 2014)

Using a model to validate the historical observation is one way for anomaly detection. A univariate model is used in (Chen, Li, Lau, Cao, & Wang, 2010) to estimate the load profiles in order to detect abnormal readings. In this paper, load anomalies are grouped into two categories: locally corrupted, which are the ones deviate from local patterns, and globally corrupted, which are the ones deviate from global patterns of the load curves. However, univariate models are not reliable when the change in a load profile is due to weather variations. In the probabilistic load forecasting track of GEFCom2014, a winning team developed a model-based anomaly detection method with a fixed threshold to clean the load data (Xie and Hong 2016a).

In addition, growing concerns about cybersecurity have pushed researchers to investigate load forecasting approaches using bad input data (Yue et al., 2019). A real-time load anomaly detection is proposed in (Luo, Hong, & Yue, 2018) for very short-term load forecasting. The method has two components: a dynamic regression model and an adaptive anomaly threshold. The proposed solution outperforms three other methods significantly in a case study using ISO New England data.

Using a robust model under data integrity attacks could improve the reliability of a power system. Three robust load forecasting models are proposed in (Luo, Hong, & Fang, 2018a) to address this challenge. The models include two customized versions of iteratively re-weighted least squares regression model and a L_1 regression model. The performance of robust models are evaluated through a case study using GEFCom2012 data resulting in a dominant performance for L_1 regression model.

Among the small number of load forecasting papers that tackle data quality issues, few of them address the data quality issues in the temperature record. Hong, et. al. (2010) discussed the data qualities associated with the historical weather data and their implications in short term load forecasting. After GEFCom2012, Hong, Wang, and White (2015) proposed a method to select appropriate weather stations for load forecasting. In the final match of GEFCom2017, Kanda and Veguillas (2019) eliminated several weather stations due to data quality concerns. A novel temperature data cleansing method is proposed in (Sobhani, Hong, & Martin, 2020). The authors adopted a load-based temperature prediction model to screen the anomalies in temperature profiles. The quality of weather data is then evaluated in a load forecasting practice.

At lower levels of a power grid, the types of data quality issues change. Few studies in the literature have addressed load data issues at MV/LV level. In (Sun et al., 2016), irregular nodes of a distribution network were detected based on the Euclidean distance between the parent and corresponding child nodes. The switching operations that are responsible for irregular nodes are detected based on how far the corresponding load forecast is from the normal patterns. Two standard deviations are used to capture deviations from the normal patterns to mark irregular load profiles.

A regression-based methodology was proposed in (Baran, Freeman, Hanson, & Ayers, 2005) to detect and fix the outliers of the meters' data at delivery points of a distribution system. The meters with the correlation factors higher than an assumed value are grouped together and the outliers are detected based on a threshold (three standard deviations away from the mean). Then, the detected anomalies were estimated by a regression function using the load data of the grouped meters.

A two-stage methodology was proposed to detect the anomalies in bus load data (Chen, Kang, Tong, Xia, & Yang, 2014). The authors assumed that the "bad data" is due to two sources; signal transmission (Null Point and zero point, consecutive constant points), system operation (Bus maintenance, load transfers). Zero points, consecutive constant points, bus maintenance, and load transfers are detected by pattern identification method and then replaced by linear interpolation. The non-obvious bad data is detected by using a typical daily load profile. The data quality was then tested through a load forecasting practice. The anomaly detection and cleansing improved the forecast accuracy by 4%.

To model unmonitored customers on LV networks, two methods are proposed in (Giasemidis, Haben, Lee, Singleton, & Grindrod, 2017). The profiles of a few monitored customers are assigned to the unmonitored ones by using the substations' data. The match between the half-hourly demands at the aggregate level and approximations to the mean daily demand of customers is optimized to find the best profiles. They used a simple average and the genetic algorithm to find the best match for the unmonitored customers. The proposed methods outperform a benchmark method (Monte Carlo). The data are preprocessed and the outliers and missing values are replaced by the average of same-day data.

As we will discuss in Chapter 3 and 4, data quality issues at the delivery point level require unique solutions, because they have specific features seen only at this level of the hierarchy. The literature suffers from a lack of a comprehensive study on delivery point load forecasting. In this dissertation, we explore data quality issues in the delivery point load profiles extensively.

CHAPTER 3: THEORETICAL BACKGROUND

3.1 Multiple Linear Regression

Regression is a statistical tool to study the dependency of one variable, *the dependent variable*, on one or more variables, the explanatory variables, in order to estimate or predict the dependent variable (Gujarati, 2003). Multiple Linear regression (MLR) is a type of regression with more than one explanatory variable in a linear regression function. By linear, we mean linear in parameters not in variables. In other words, the variables with any transformation are plugged in a linear function with linear parameters.

MLR has been widely used in load forecasting practices. Two types of forecasting models are used in this dissertation including load forecasting and temperature forecasting models. Both models are regression-based ones with multiple independent variables in a linear function.

There are many methods for estimating the parameters of a regression function. The method of ordinary least squares (OLS) is popular and strong. The general linear regression model, in terms of X as the explanatory variables, is defined:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_{p-1} X_{i,p-1} + u_i \tag{3-1}$$

where, $\beta_0, \beta_1, \ldots, \beta_{p-1}$ are the regression parameters; X_{i1}, X_{i2}, ..., $X_{i,p-1}$ are explanatory variables; u_i is the error term, and $i = 1, 2, \ldots, n$.

Under certain assumptions, the response function for regression model is shown in equation 3-2. OLS estimates the parameters by minimizing the square errors (eq. 3-3)

$$\widehat{Y}_i = \widehat{\beta_0} + \widehat{\beta_1} X_1 + \widehat{\beta_2} X_2 + \cdots + \widehat{\beta_{p-1}} X_{p-1} \tag{3-2}$$

$$\min \sum_{i=1}^{n} \hat{u}_i^2 = \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \tag{3-3}$$

The estimates by OLS are called Best Linear Unbiased Estimates (BLUE) under certain assumptions. The classic linear regression model (CLRM) has seven fundamental assumptions for MLR to make BLUE estimates. The assumptions are as follows (Gujarati, 2003):

1- The regression model is linear in the parameters (not necessarily linear in variables)
2- The explanatory variables are independent of the Error term: $cov(X_i, u_i) = 0$
3- Zero mean: $E(u_i|X_i) = 0$
4- Homoscedasticity: $var(u_i) = \sigma^2$
5- No Autocorrelation between errors: $cov\left(u_i, u_j\right) = 0$
6- The number of observations must be greater than the number of explanatory variables
7- The observations' values must not be all the same: $var(X_i) > 0$
8- No perfect collinearity between two explanatory variables
9- There is no specification bias.

In the regression models, there are two types of explanatory variables including quantitative and qualitative variables. Quantitative variables explain the variations of a factor with a value for each observation. On the other hand, the qualitative variables are defined by using dummy variables. The variables such as the month of a year or day of a week are assumed to be categorical variables in the models we use here. However, advanced statistical software such as SAS, R or Python has the capability to take care of categorical or class variables by assigning dummy variables automatically.

3.2 Error Metrics

There are different types of error measurements in the literature. Depending on the applications and interpretation purposes, the error metric could be different. In this research, we use three metrics for the error measurements. Error, Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are two metrics for the prediction error that we use here.

$$error_i = Y_i - \widehat{Y_i} \tag{3-4}$$

$$MAE = \frac{100}{n} \sum_{i=1}^{n} \left| Y_i - \widehat{Y_i} \right| \tag{3-5}$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{Y_i - \widehat{Y_i}}{Y_i} \right| \tag{3-6}$$

where Y_i is the actual values, Y_i is the predicted values and *n* is the number of observations.

3.3 Error Diagnosis

In a binary classification testing, typically, two factors are used to measure the performance of the testing. False positive and false negative errors check the accuracy of the test results and measure the detection performance. In statistical hypothesis tests, these errors are called type I and type II. In this research, we use these two factors to evaluate the performance of the proposed detection methods.

False positive error is a test result where a normal situation is detected as a failure (or any condition, which is not). False negative is the failure situations that are not detected in a test. In addition, to better quantify the detection performance, we use false positive ration (FPR) which is the number of false positive errors to total number of normal observations and false negative ratio (FNR) is the number of false negative errors to all failure observations. A higher FPR indicates that the detection method marks more normal observations as a failure and a high FNR determines that the method has less capability to detect failures.

3.4 Greedy Algorithm

Greedy is an algorithm paradigm based on a heuristic approach to find the best solution using a reasonable number of steps. In other words, the greedy algorithm is a heuristic optimization method to lower the calculation costs in order to achieve an acceptable solution. In an optimization process, the total number of steps to get to the global optimum is dependent to the method. The number of steps and their complexity makes the whole process more costly.

A greedy strategy may not lead to the global optimum and it could fall into a local one, but the main purpose is to have a lower number of steps in a quicker procedure. In each step towards the optimum, the greedy algorithm selects the most possible candidate using a selection function. This function sacrifices other routes with lower chances of getting to the optimum point.

Therefore, in a greedy algorithm, we need five components including a candidate set, a selecting function, feasibility criteria, an objective function, and a solution function.

By customizing the selecting function and the feasibility criteria, we can have different paces towards the optimum point.

On the other hand, since a greedy algorithm does not test all possible routes to get to the global optimum, it is highly likely to fall into a local optimum. In the cases where the procedure of the optimization process is costly, using a greedy approach is more reasonable. In this research (Chapter 5), we develop a customized greedy algorithm to propose an alternative approach with lower labor costs for load transfer detection.

CHAPTER 4: DATA

In this research, we conduct the experiments using the data from a power utility. The service territory of the utility is a large geographical area in the United States. It is divided into 26 load zones in addition to a control center. Each zone has a few substations at distribution level that supply power for a number of consumers. These substations are called delivery points and there is a meter at each delivery point measuring electric flow for the corresponding substation.

Hourly load data are available in this dataset for a total of 428 meters. The number of meters in a zone ranges from 2 to 47. The dataset covers 11 years of history from 2006 to 2016. Load data of the meters have different lengths of history, ranging from one to eleven years. Thirty two retired meters are also included in the dataset. Figure 4.1 shows a schematic diagram of the load distribution at the service territory.

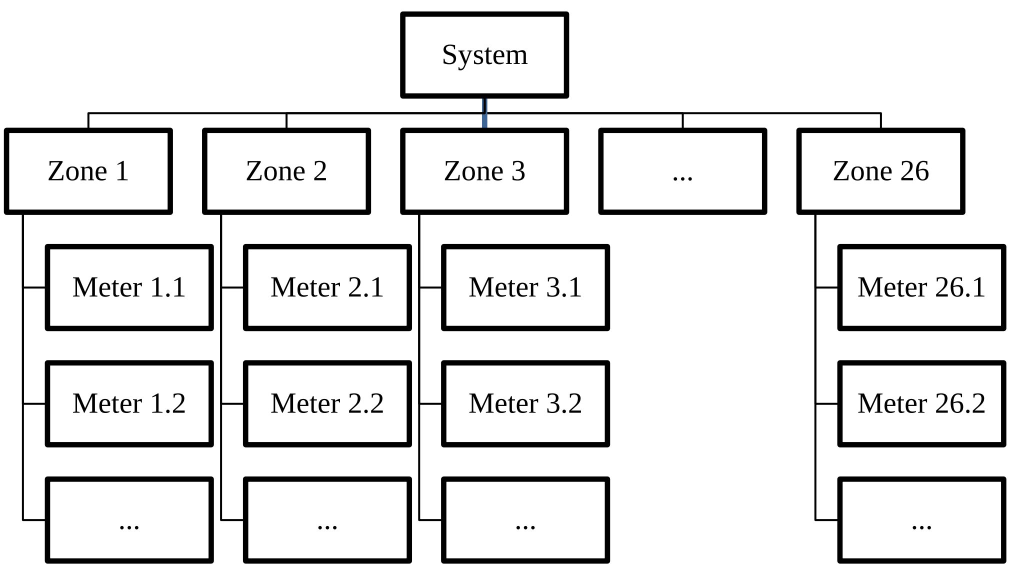

Figure 4.1: The schematic diagram of the load distribution is the service territory

The power utility purchases weather data from two vendors. The first vendor reports the data from 10 weather stations while the second one covers 28 stations. The weather stations are located across the service territory. In this research, we mainly use the hourly readings of temperature reported by vendor 2, because of the larger number of stations. This chapter presents an analysis of the dataset by providing some preliminary statistics for the load and weather data.

4.1 Load Data

The load data have three levels of aggregation (Figure 4.1): system level, load zone level, and delivery point level, which have 1, 26 and 428 members respectively. The members are not equally distributed over the load hierarchy. It means that although the members of a given level are at the same stage, the load profiles do not have similar load levels. In this section, we analyze the load data to provide a perspective for the properties of the profiles at different levels of the hierarchy.

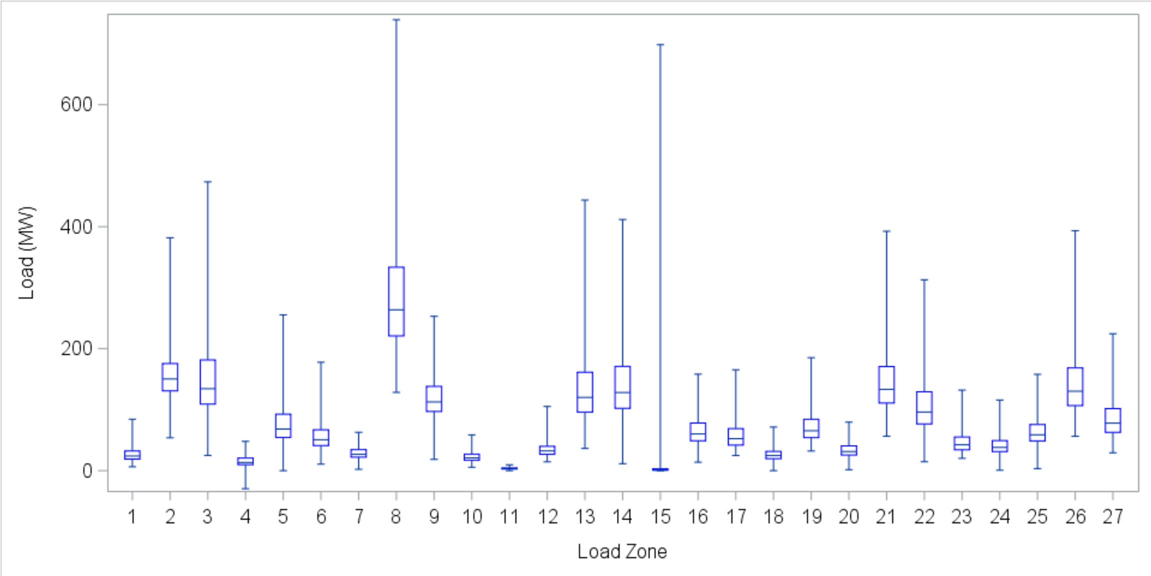

Figure 4.2: Grouped boxplot of the load at each load zone

Figure 4.2 depicts the statistics of the load at each zone for the whole 11 years of data. As we can see, the characteristics of the load at different zones are various. This is due to the corresponding service zone and number of consumers covered by a load zone. In this research, we analyze each load zone individually and we assume that there are no interactions between to load zones such as load transfer between two meters in two different zones.

The second level of hierarchy belongs to the delivery points. The detailed data availability and simple statistics for all zones and meters are provided in Appendix A. In this section, we analyze the load data for a sample zone to provide a perspective to the load profiles of the delivery points. The sample zone is Zone 9 with 13 meters. The majority of consumers belong to the residential sector. This can be observed in the correlation between the temperature and load shown in Figure 4.3 and Figure 4.4.

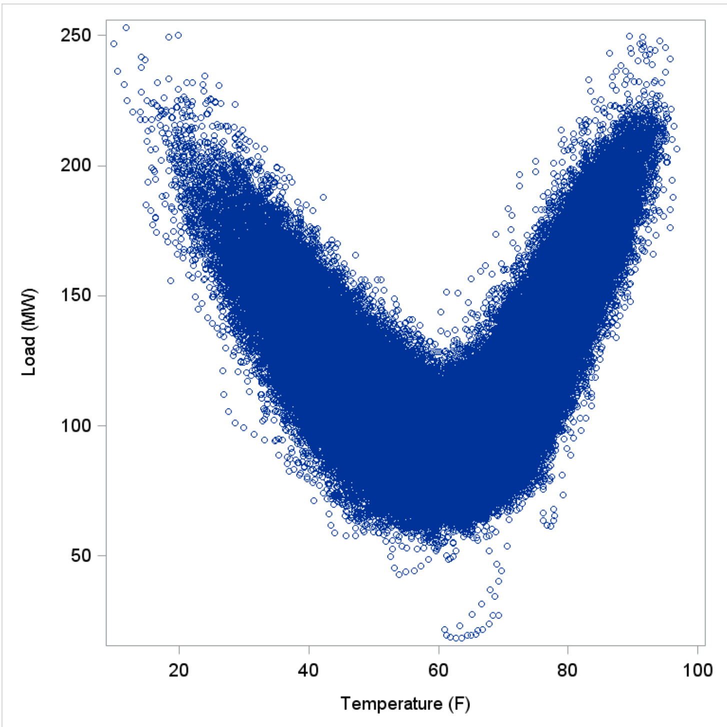

Figure 4.3: The scatter plot of load against temperature for Zone 9.

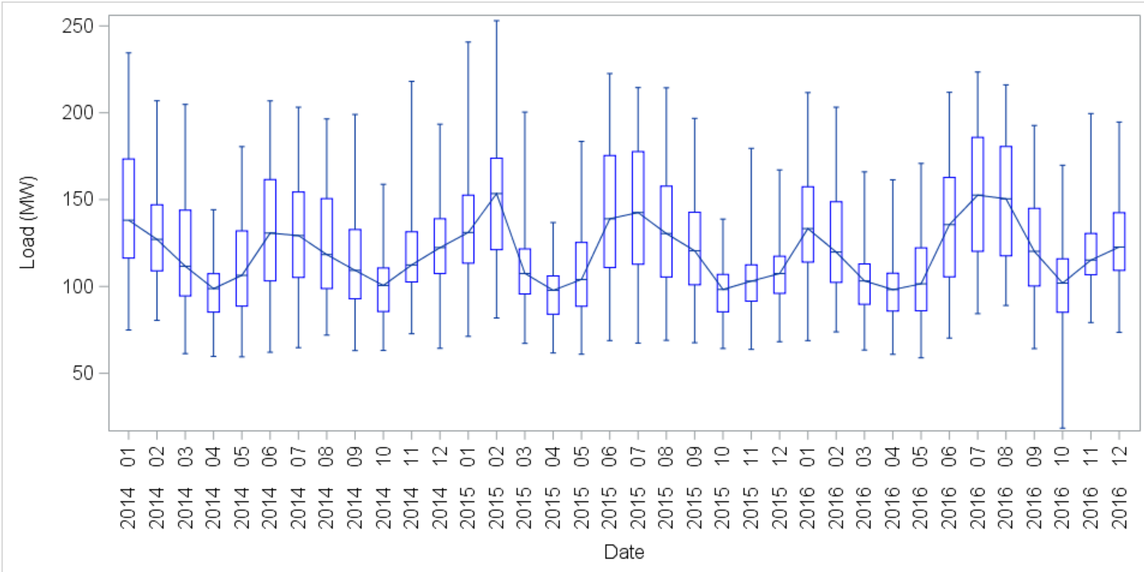

Figure 4.4: The grouped boxplot for the load time series in Zone 9.

Table 4.1 shows the availability of the data for these meters in the period between 2006 and 2016. “Yes” means that the meter has at least one reading in that year and “No” means that there is no record for the whole year. Among 13 meters, five of them have full years of data and the rest are younger meters with a shorter history. Twelve meters are still operating and one meter (Meter 9.10) seems to have been retired in 2015.

Table 4.1: Data availability in the meters of a sample load zone

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Zone 9	9.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.7	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.8	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.9	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	9.10	No	No	No	No	No	No	No	Yes	Yes	Yes	No
	9.11	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
	9.12	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
	9.13	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Table 4.2 shows the statistics of the load data for the meters of Zone 9. The average load is an indicator of the load level in each meter. The value of the average load in a meter is highly related to the number of customers supplied through the corresponding delivery point. For example, the average loads of meter 9.10 to 9.13 are too low in comparison to the other meters. Therefore, we should expect higher randomness in these meters due to the aggregating of a lower number of household load profiles. In addition, we can see that the minimum load of each meter is zero, which is evidence for possible outages in all meters. The statistics do not reveal further information about the characteristics of the meters' load profiles.

Table 4.2: Statistics of the load data in the meters of Zone 9 (in kWh).

Meter Code	Available Period (years)	Non-zero readings (%)	Mean	Std.	Min.	Max.
9.1	11	95.0	11488	6159	0	54300
9.2	11	98.6	15881	9639	0	51467
9.3	11	97.6	14663	7524	0	51408
9.4	11	94.9	11489	6159	0	54300
9.5	11	96.8	24963	11023	0	65167
9.6	11	98.0	16007	7353	0	60804
9.7	10	99.6	26487	6694	0	49280
9.8	9	95.7	2017	2471	0	10115
9.9	9	99.2	2436	2606	0	10122
9.10	3	0.1	23	680	0	22523
9.11	4	74.2	139	103	0	477
9.12	4	44.5	251	307	0	773
9.13	4	91.5	428	180	0	575

The line plots of the load profiles are shown in Figure 4.5. The profiles are for the hourly loads in 2014, while all meters were operating. The diversity of the load profiles demonstrates the high randomness in delivery point load data. Furthermore, we can find some obvious anomalies in the data by a quick visual inspection. For instance, we can see a long gap in meter 9.2 or a significant drop and raise in meter 9.3. Meter 9.7 and 9.9 look like to be industrial load profiles, because the load does not show a strong correlation with the temperature variations through a yearly timeframe. In most days of the year, meters 9.8 and 9.10 do not have considerable loads. The load profiles of the last three meters are low and very noisy, which is probably due to their immature loads.

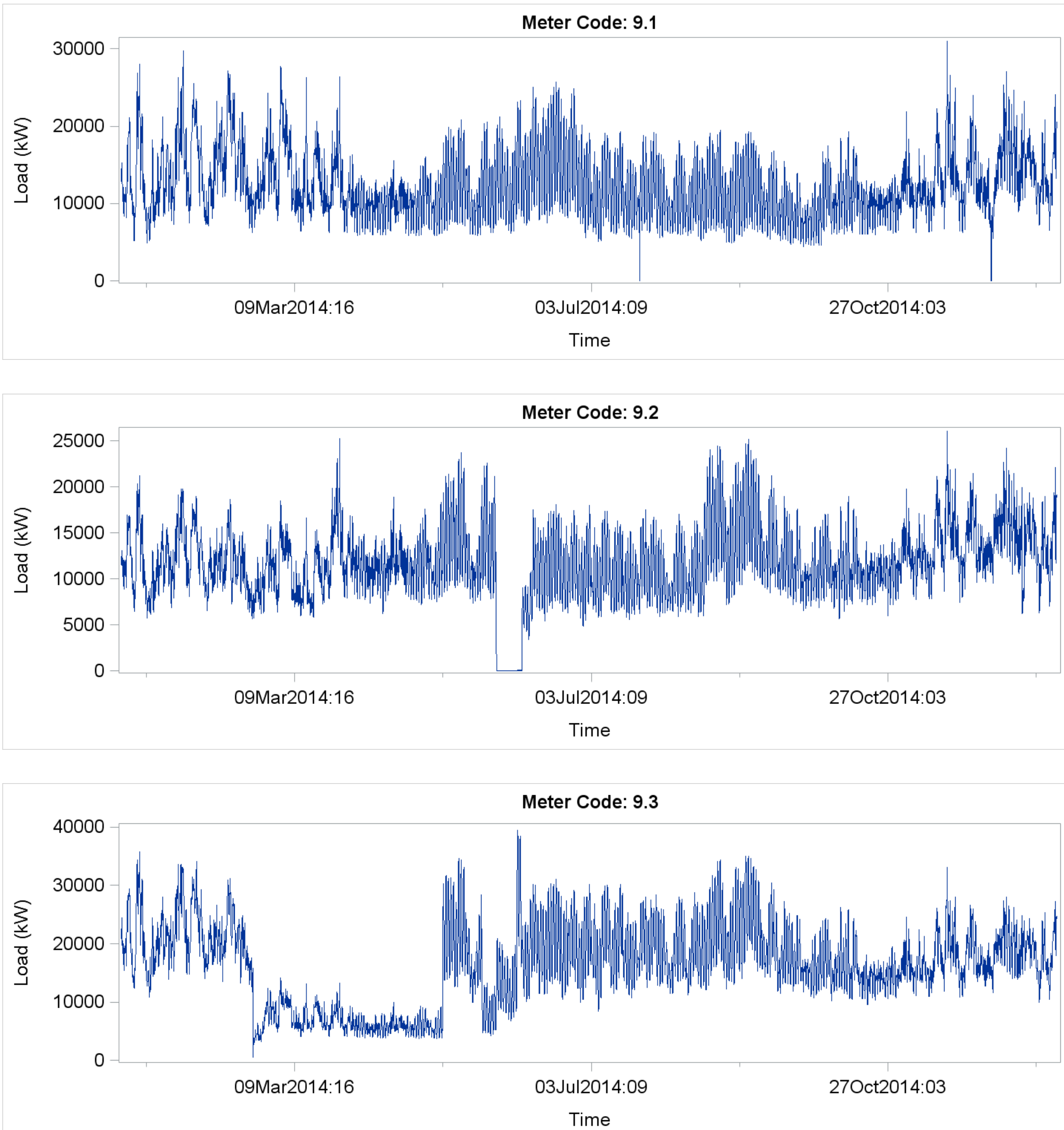

Figure 4.5: Load profiles of 13 meters in COOP 9 for the year 2014.

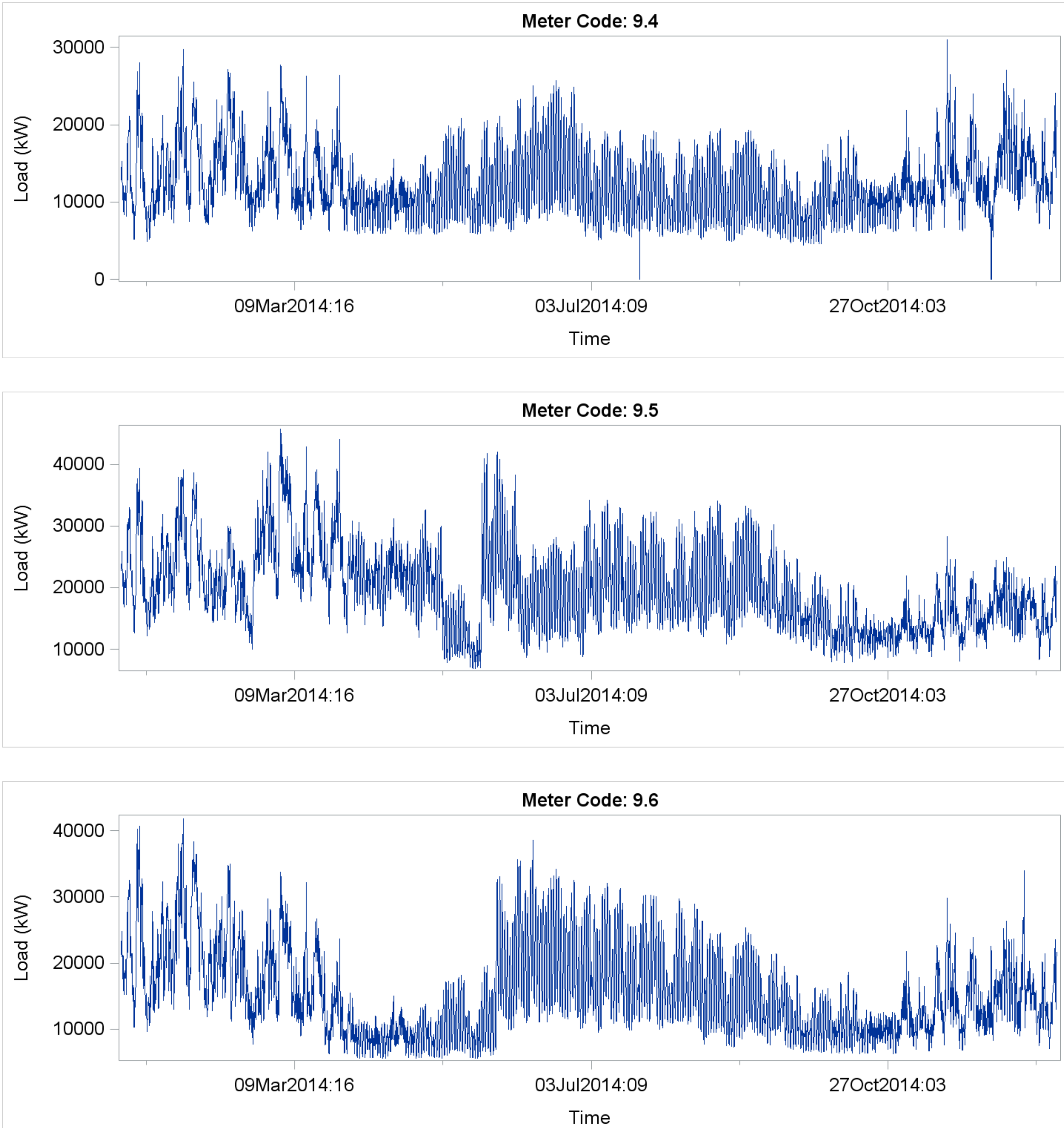

Figure 4.5.cont. Load profiles of 13 meters in COOP 9 for the year 2014.

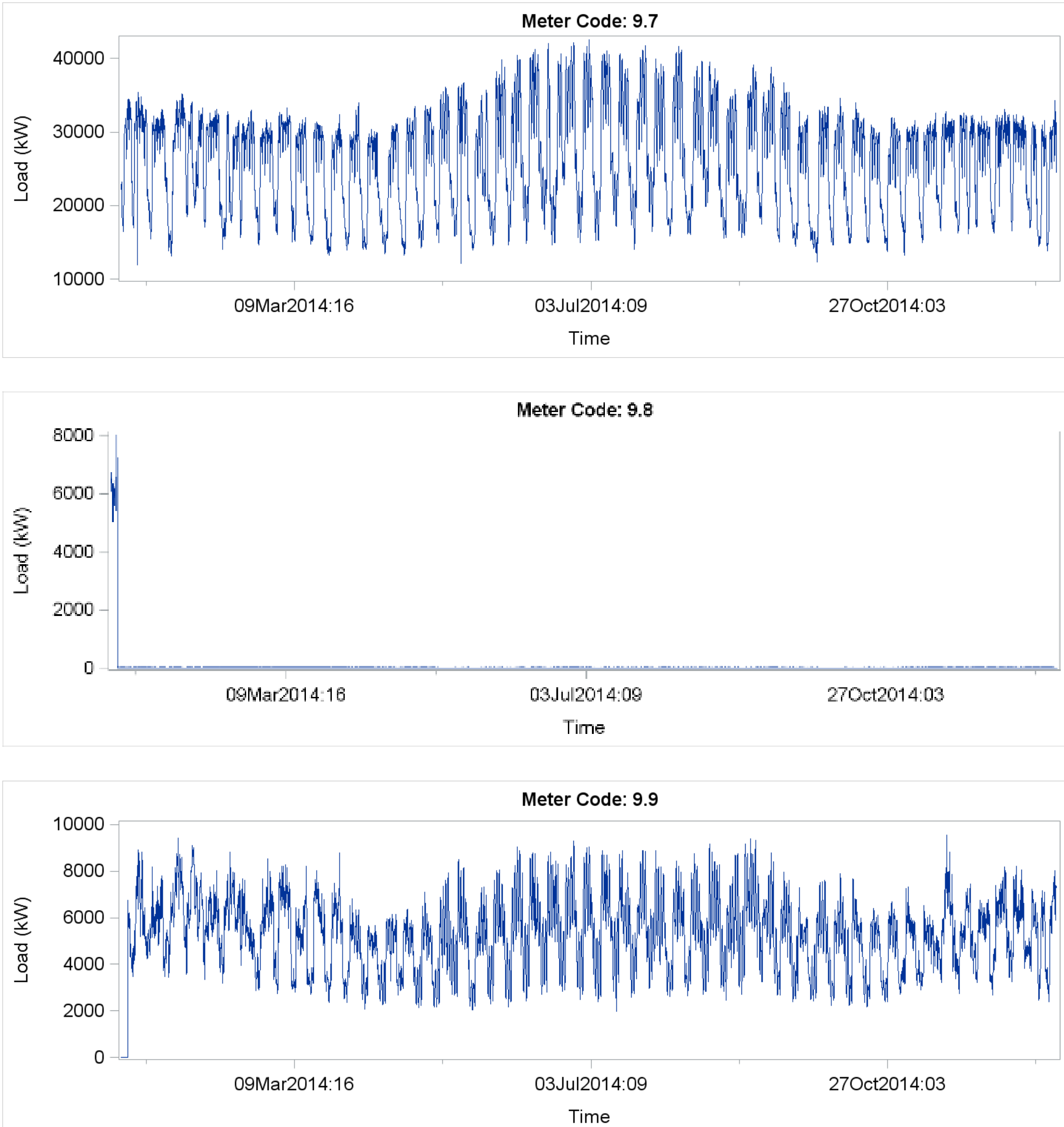

Figure 4.5.cont. Load profiles of 13 meters in COOP 9 for the year 2014.

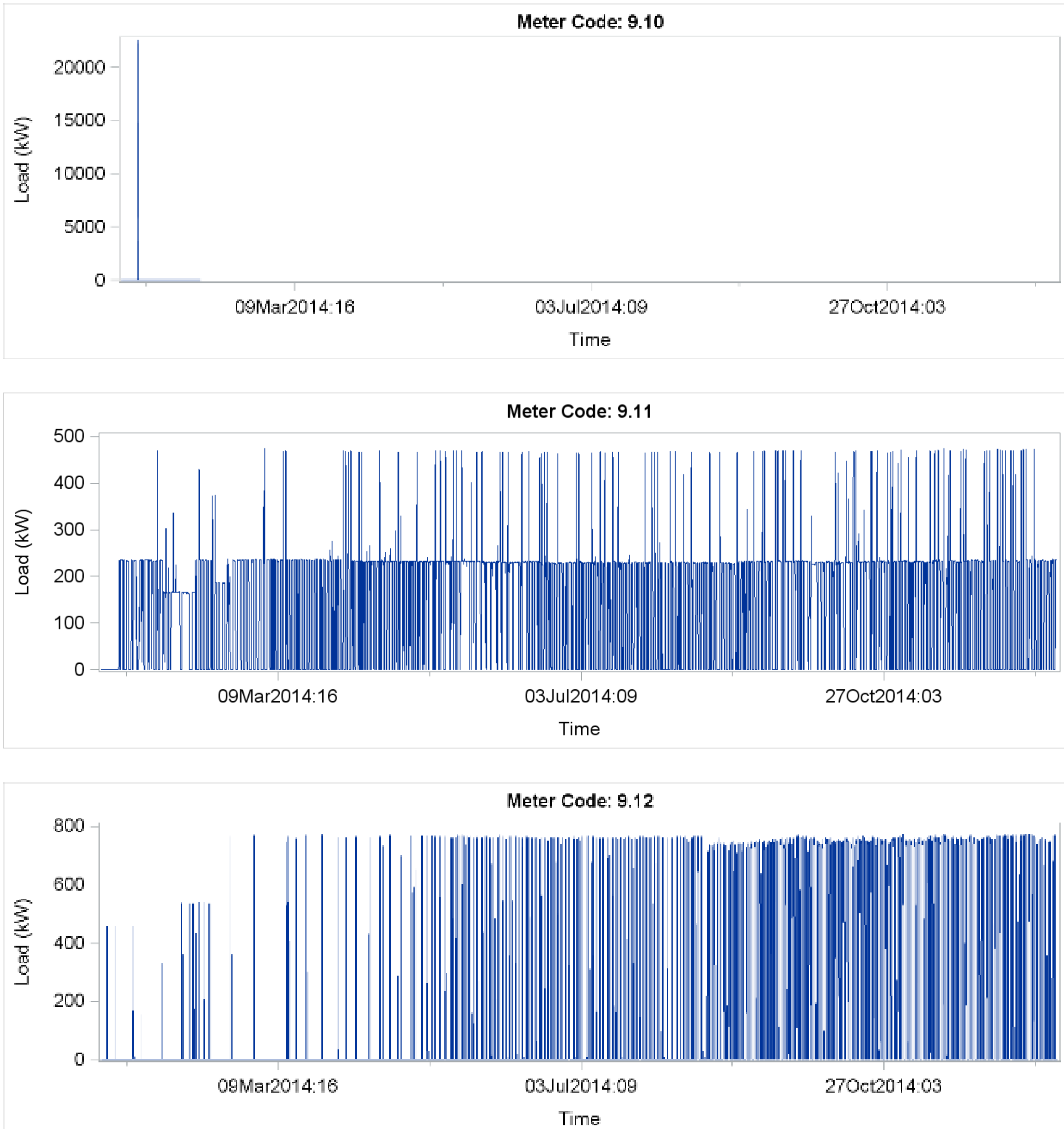

Figure 4.5.cont. Load profiles of 13 meters in COOP 9 for the year 2014.

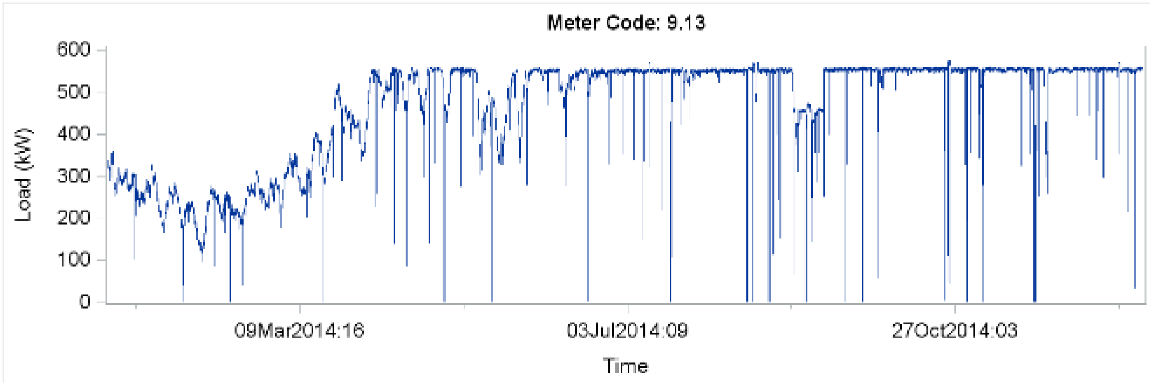

Figure 4.5.cont. Load profiles of 13 meters in COOP 9 for the year 2014.

The load profiles in other zones and meters (Appendix A) have similar properties and issues. The simple investigations we did in this section open a window to study the salient features of the load profiles at the delivery point level. Data quality issues play a vital role in analyzing the load data at this level of the hierarchy. Later, we dig deeper into the data to make a comprehensive study on the delivery point load forecasting.

4.2 Weather Data

The utility purchases weather data from two vendors. The vendors acquire the data from the readings of multiple weather stations across the service zone. Vendor 1 and Vendor 2 report the data from 20 and 28 weather stations respectively while they share 14 stations. The weather stations are located in different locations to provide a thorough assessment of the weather conditions for all load zones.

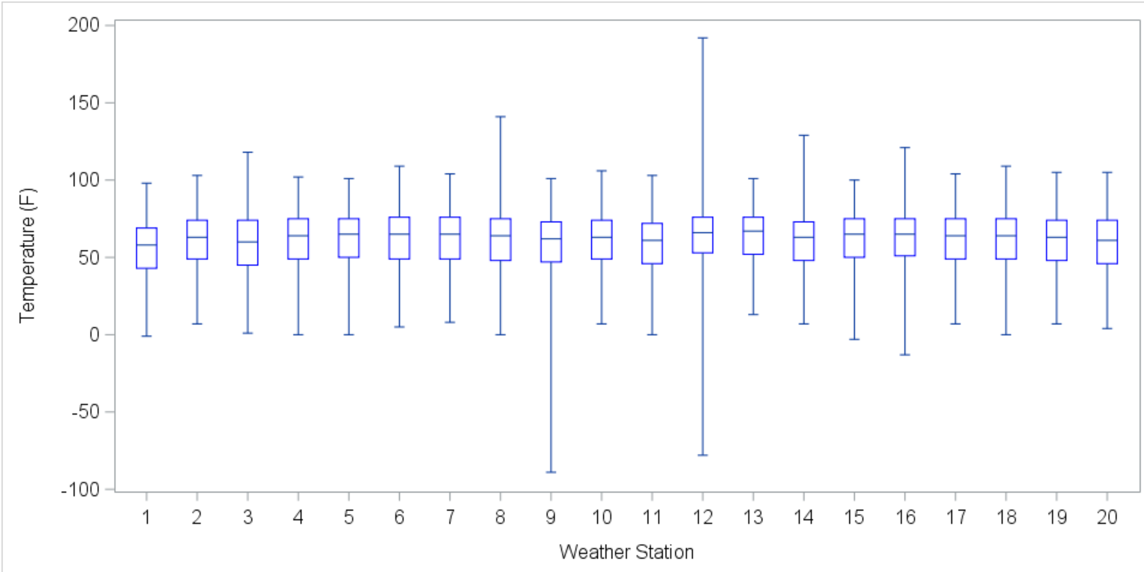

Figure 4.6: Grouped boxplot for the temperature distribution in different stations reported by Vendor 1

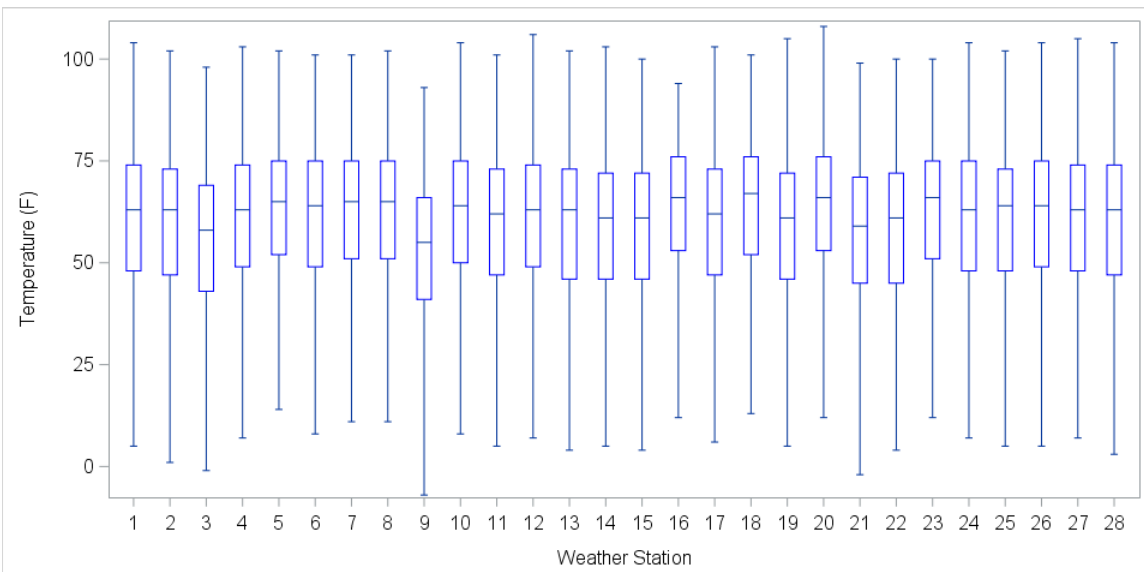

Figure 4.7: Grouped boxplot for the temperature distribution in different stations reported by Vendor 2

Figure 4.6 shows the simple statistics of the temperature time series for 20 weather stations reported by Vendor 1. The average and standard deviations of the temperature in different weather stations range approximately close to each other. Consider that the average temperatures of 11 years data do not reflect accurate differences between the temperature time series. In addition, we see some unusual numbers in low temperature values at some stations. Although the mean temperatures are almost constant in all stations, in some stations the minimum temperature is too low. In addition, assuming that the reports are correct, having a temperature as low as -89^{o}F is an unusual number. This could be an evidence for potential anomalies in the weather data.

On the other hand, Figure 4.7 illustrates a boxplot for temperature distribution in 28 weather stations reported by the Vendor 2. Consider that the same numbers for weather stations in two boxplots do not represent similar stations. We can see the average temperature in stations of Vendor 2 is almost similar to ones in Vendor 1. However, the deviations of temperature are not fluctuating in Vendor 2. It means that the reports by Vendor 2 are more accurate and the data have a filtering process before reporting.

To confirm the possibility of anomalies in the temperature data, we made a simple test. We compared the temperature profiles of two vendors in the shared weather stations to find any differences. The temperature profiles reported by two vendors from a single weather station were identical in many cases. On the other hand, we found considerable samples that the temperature profiles are completely different. Figure 4.8 illustrates three examples of the aforementioned temperature profiles. Both time series are from a single weather station in the exact same timeframe. As we can see, the profiles are respectively different.

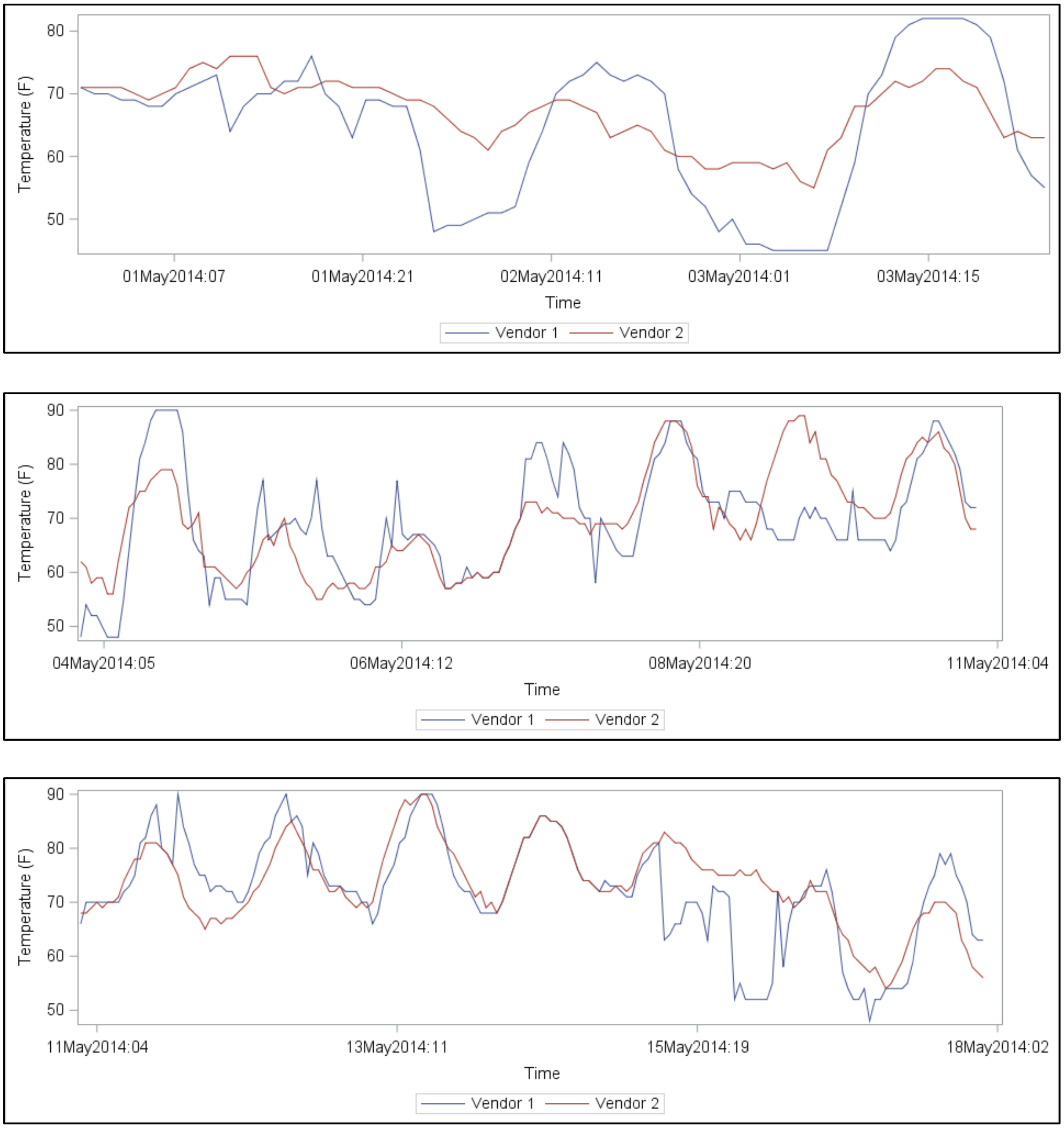

Figure 4.8: Temperature profiles from a given weather stations by the two vendors

In the chapter 8, we explore the weather data in order to prepare them for the load forecasting process. We propose a methodology inspired by (Sobhani et al., 2020) to improve the weather data quality using multiple load zones.

CHAPTER 5: LOAD TRANSFERS

Real-world data always contain some quality issues such as anomalies, outliers, and missing values. In a power system hierarchy, data quality issues of the load profiles vary in different levels of aggregation. For example, due to the malfunction of an electric meter in a household, missing values will be reflected in the corresponding load profile. If we move to the higher levels of the hierarchy, as we aggregate the load profiles of single households to generate the load profile of a building block, we will not identify the missing values of the aforementioned household. Therefore, these missing values are data quality issues at the household level, but not at the building block level. Hence, we cannot expect similar types of data quality issues in all levels of a load hierarchy.

At delivery point level, outages and load transfers are two major data quality issues. An outage is typically a local event. Falling of a tree, contact of a squirrel, lightning, or equipment failure can cause temporary and typically short outages in one or a few neighborhoods. These outages usually occur in limited areas of the service zone and are reflected in the reading of substations' meters. On the other hand, power system operators, due to some reasons, transfer load between different delivery points to improve systems reliability. A load transfer changes the shape of a normal load profile vividly and affects the quality of the load data. In this chapter, we propose a novel methodology for load transfer detection.

5.1 Properties

A load transfer is a typical load management task at a low/medium voltage level to increase the reliability of the system. An equipment failure or inspection outage can result in transferring a portion of the load to another substation. Maintenance of the equipment, change of the network structure, extension of the distribution territory, and retirement of a meter are some other reasons for load transfers (Gu & Jiang, 2017). A load transfer can be either permanent, seasonal or temporary. Depending upon the situation, all or a part of the load may be transferred. Most of these transfers are between two meters, although sometimes load may be transferred among several meters.

Load transfers are a major source of data quality issues at the delivery point level. Load transfers change the shape of load profiles that affects the performance of load forecasting and other data analysis tasks.

This research proposes two methods, a model-free method (MFM) and a model-based method (MBM), to detect the load transfers between two delivery points of a distribution network. Both methods are based on the simple idea that aggregating the meters with load transfers offsets the transfers. We first explore the features of load profiles to screen the meters with abnormal shapes. We then detect the best match for a load transfer by pairwise grouping the meters. MFM employs standard deviation as the measure to detect the correct paired meters. The MBM characterizes the load profiles using a regression model.

Distribution engineers typically log load transfers manually. Inconsistent logging practices and the natural error that can happen with any human process leave plenty of room for inaccuracies in the load transfer log. Some load transfers go unlogged; some logged transfers cannot be verified by the load profile. We manually checked the entire dataset by visual inspection of the load profiles and identified 177 load transfers between the meters. In this section, we will present some salient characteristics of these transfers. In Section 5.3 , we will develop simulations based on these characteristics to assess the performance of the proposed method. It should be noted that the manual check and visual inspection have their own drawbacks. Similar to any other detections, the visual inspection could have false negative and positive errors. The identified transfers are the ones with respectively significant drop and raise in load profiles. However, some transfers could be hidden in yearly load profiles.

The load transfers are studied year by year. Among all transfers, 75% of them were temporary and the rest were permanent. Temporary means that the load transfer will be back to the original delivery point sometime in the future but in a permanent transfer the original meter is become retired. In 63% of the identified load transfers, the total load was transferred from one meter to another. We call them complete load transfers in this study. In the remaining 37%, a portion of the load was transferred which are called partial transfers. Even in these partial transfers, on average, more than 80% of the total load was displaced.

Figure 5.1 shows the histogram of the durations for the temporary transfers. Most temporary transfers take place in less than a month, which is mostly due to planned maintenance or because of an emergency when equipment needs to be de-energized. Figure 5.2 depicts the number of load transfers started each month. While the frequency of load transfers is not uniformly distributed over a year, most transfers start in March, April, and October, which are the months before the summer and winter's peak loads. Figure 5.3

shows the frequency of load transfers in each year for a given load zone. Most zones only have one or two load transfers in a year. It is rare to see more than three transfers per year. A few zones do not have any load transfer.

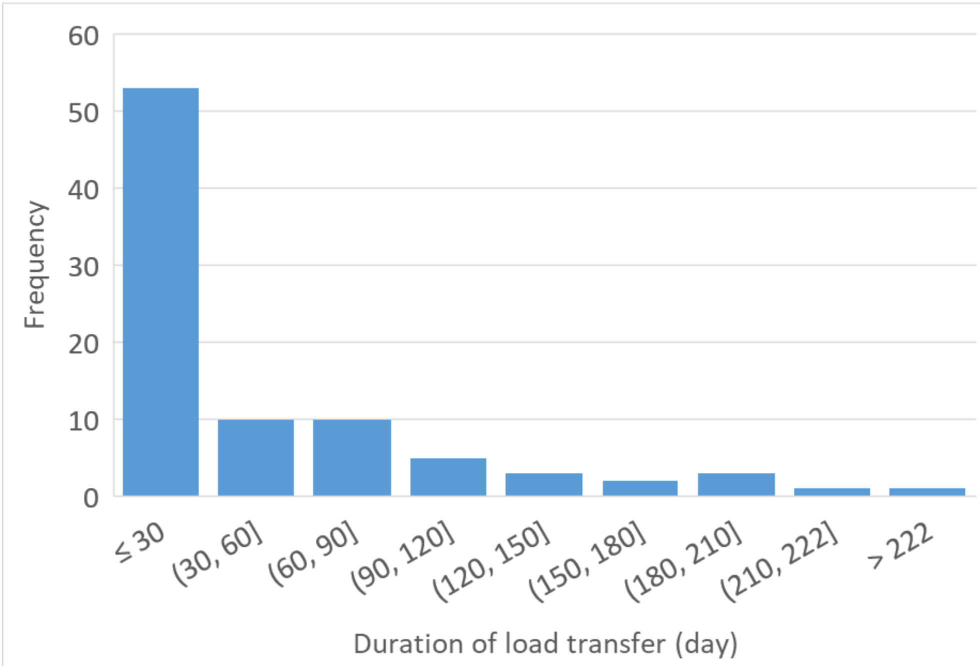

Figure 5.1 Distribution of load transfer durations for temporary transfers

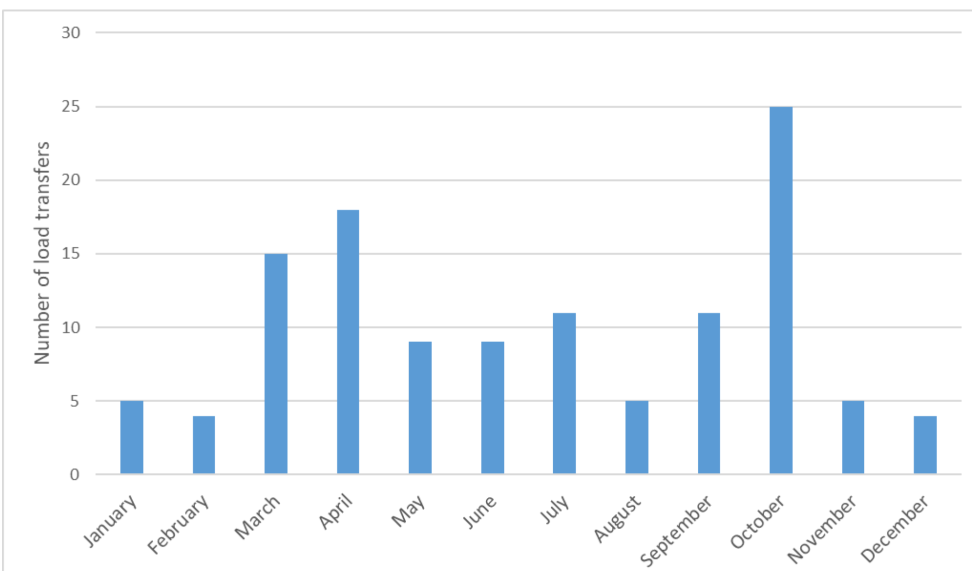

Figure 5.2 Distribution of starting point month of load transfers.

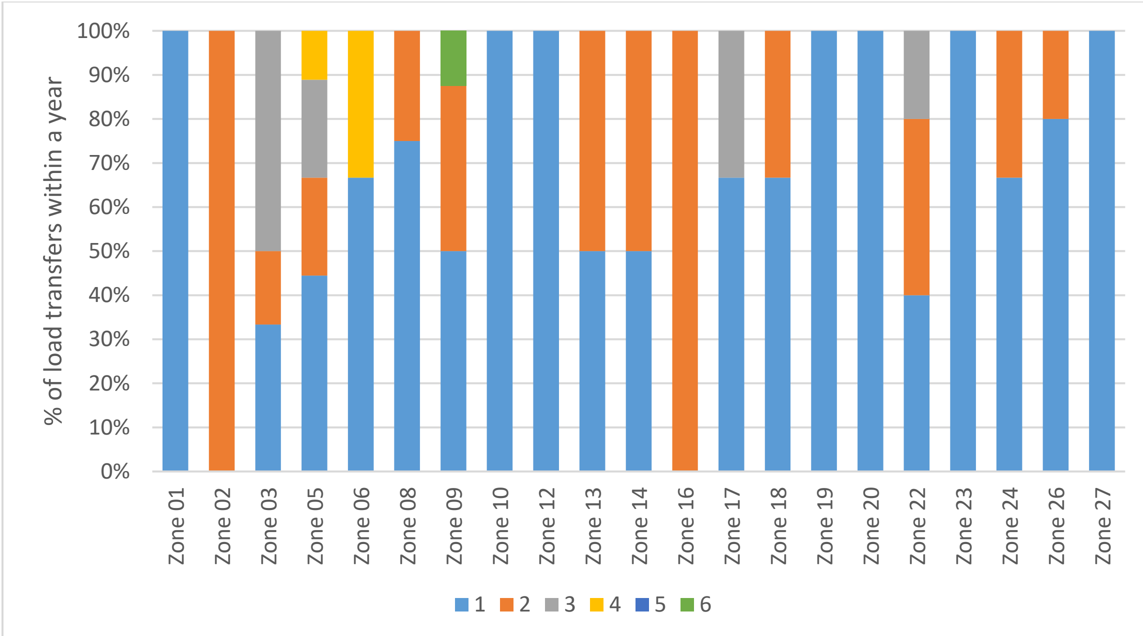

Figure 5.3 Percentage of load transfer times per year

5.2 Methodology

We propose two methods for load transfer detection. The core idea is inspired by the fact that aggregating the meters with load transfers offsets the transfers. The first one is model-free, which utilizes simple statistics of the load data to screen meters with load transfers. The second one is model-based, which digs deeper into the data to have a better judgment on the meters with load transfers.

5.2.1 Model-free load transfer detection

Load transfers can shift load profiles upward or downward. These unusual elevations and drops change the distribution of the load data when compared to a normal load profile. To capture such structural breaks in the load profiles, we employ the standard deviation as a measurement factor. The standard deviation does not reveal much information regarding the load transfers, but a pairwise comparison can screen the potential groups of meters with load transfers. For a given pair of meters, the standard deviation of their aggregated load versus the sum of individual standard deviations of each meter's load should not be different if there was no load transfer. We measure the rate of this difference by indexing and ranking the pairs as explained below.

To implement this methodology, we investigate the load data of all pairs of the meters in a given year and take the following steps:

1) In each pair, calculate the standard deviation of each individual meter and the one for the corresponding aggregated load.
2) Rank the pairs of meters based on an index to prioritize the pairs with the stronger potential of a load transfer.

We propose a model-free index (MFI) for the ranking of the meter pairs. For a group of two meters, the MFI is defined as follows:

$$MFI = \frac{STD_{agg}}{STD_i + STD_j} \tag{5-1}$$

where STD_i and STD_j are the standard deviations for loads of the two meters, STD_{agg} is the standard deviation of the aggregated load. We then rank the pairs based on the MFI. The pairs with a lower index value have a higher potential of a load transfer.

5.2.2 Model-based Load Transfer Detection

The Model-Based Method (MBM) improves the model-free detection by leveraging a load forecasting model that can extract additional salient features of the load profiles. It is based on the same idea that the aggregated load offsets the load transfers.

When fitting the same load forecasting model to different load profiles, the ones without load transfers are more likely to have lower in-sample-fit errors than the ones with load transfers. Furthermore, if we aggregate two meters that transfer loads among each other, the aggregated profile tends to have a lower in-sample-fit error than the individual ones do. Therefore, the methodology includes three stages:

1) Use a load forecasting model to fit each individual load profile and calculate the in-sample-fit errors;
2) Group the meters, fit the same model to each aggregated profile, and calculate the in-sample-fit errors;
3) Compare the in-sample-fit errors of the aggregated and the corresponding individual profiles, and select the meter groups with biggest changes as candidate load transfers.

Before implementing the methodology, we have to specify four components: a load forecasting model, a measure for in-sample-fit error, a method to pair weather stations with the individual meters and meter groups, and an index to rate the changes of in-sample-fit error due to aggregation. The scope of this paper does not include the refinement of each component to reach optimal detection results, but on proposing a methodological framework for load transfer detection. To stay focused on the proposed load transfer detection methodology, we keep these components as simple as possible.

We use the Vanilla model as the load forecasting model. The Vanilla model was used as the benchmark model in the series of Global Energy Forecasting Competitions (Hong, Pinson, et al., 2014)(Xie & Hong, 2016)(Hong et al., 2019). It is a multiple linear regression model that includes a third-order polynomial coincident temperature, calendar variables, and their interactions. The Vanilla model can be specified as follows:

$$L_t = \beta_0 + \beta_1 Trend + \beta_2 M_t + \beta_3 W_t + \beta_4 H_t + \beta_5 W_t H_t + \beta_6 T_t + \beta_7 T_t^2 + \beta_8 T_t^3 + \beta_9 M_t T_t + \beta_{10} M_t T_t^2 + \beta_{11} M_t T_t^3 + \beta_{12} H_t T_t + \beta_{13} H_t T_t^2 + \beta_{14} H_t T_t^3 \quad (5\text{-}2)$$

where L_t is the load forecast for time *t*; β_i are the coefficients estimated using the ordinary least square method; M_t, W_t and H_t are classification variables of the coincident month-of-the-year, day-of-the-week, and hour-of-the-day for time t respectively and T_t is the coincident temperature.

We use the mean absolute percentage error (MAPE), which is widely used in the load forecasting research and practice, as the measurement of in-sample-fit error (eq. 3-6). We pair each meter with the weather station that offers the best in-sample-fit MAPE. For a meter group, we use the average temperature from the weather stations paired with each individual meter within the group.

We propose a model-based index (MBI) to rank the meter groups. The MBI for a given group of two meters is defined as follows:

$$MBI = \left(\frac{MAPE_{agg}}{MAPE_i}\right)^2 + \left(\frac{MAPE_{agg}}{MAPE_j}\right)^2 \quad (5\text{-}3)$$

where *MAPEi* and $MAPE_j$ are the in-sample-fit errors for loads of the two meters and $MAPE_{agg}$ is the in-sample-fit error for the aggregated load. A lower *MBI* value implies a more significant improvement in the in-sample-fit due to load aggregation. The ratios are squared to amplify significant improvements.

To screen a given year of load and weather data for a load zone, the proposed method can be implemented in the following 6 steps:

1) Select weather station(s) for each meter;
2) Estimate the Vanilla model for each load profile and the corresponding temperature profile, and calculate $MAPE_i$;
3) Group the meters to form all possible pairs, and calculate the load and temperature for each meter group;
4) Estimate the Vanilla model for each meter group and the corresponding weather stations, and calculate $MAPE_{agg}$;
5) Calculate *MBI* for each meter group;
6) Select the groups with $MAPE_{agg}$ smaller than both $MAPE_i$, sorting the selected groups based on their MBI values from smallest to largest.

Like most, if not all other, detection algorithms, this proposed methodology is not expected to offer perfect precision. Nevertheless, executing this method gives engineers, planners and data analysts the opportunity to narrow down the candidates of a load transfer to a small number. A visual inspection that compares the load profiles of the meters in a group will eventually confirm the occurrence of the load transfer.

5.3 Experiments

A. A Medium-Size Load Zone

We illustrate the proposed methodology by applying it to the same zone that we discussed in Section 4.1 Zone 9 is a medium-size load zone, which has 9 operating meters in the year 2009. The meters measure the load of the delivery points that supply power to the residential and industrial customers.

Table 5.1 shows the results of the load transfer detection by the MFM for 2009. The groups of meters are sorted based on MFI values. The top pairs with lower index values are expected to have a higher likelihood of experiencing load transfer(s).

Table 5.2 shows a heat map of the MAPE values for all meters during the period of 2006 to 2016, which are the results of Step 2 of MBM. A cooler color (green) indicates a lower MAPE value, while a warmer color (red) indicates a higher MAPE value. For a given meter, a sudden increase in MAPE over the time raises a flag for a possible load transfer. For instance, meter 6 sees its MAPE being doubled in 2009 and 2010, which could be due to load transfer. At this stage, we cannot tell for sure whether it is a load transfer, because other abnormal events, such as major outages, may lead to increased MAPE as well.

We then aggregate the meters to make all possible pairs. For each pair, the load becomes the sum of the meters, while the temperature is the average of the corresponding weather stations. If there were load transfers between the meters, the aggregate load would offset the transfers because the resulted profile reflects the total load regardless of the shapes of individual profiles. Therefore, the MAPE of the meter group is expected to be lower than the MAPEs for the individual meters. Table 5.3 shows the top meter groups sorted by their *MBI* values in ascending order. A smaller *MBI* value means more significant improvement via load aggregation.

Table 5.1: the standard deviations of the grouped meters

Meter$_i$	**Meter$_j$**	**STD$_i$**	**STD$_j$**	**STD$_{agg}$**	**MFI**
8	9	1080	952	767	0.38
3	5	7864	10084	9958	0.55
3	7	7864	6152	10148	0.72
6	7	7207	6152	10339	0.77
3	4	7864	4956	10193	0.80
1	3	4956	7864	10193	0.80
4	7	4956	6152	8872	0.80
1	7	4956	6152	8872	0.80
2	3	3335	7864	9092	0.81
5	6	10084	7207	14153	0.82
2	7	3335	6152	7767	0.82
5	7	10084	6152	13471	0.83
2	9	3335	952	3594	0.84
2	6	3335	7207	8886	0.84
1	6	4956	7207	10409	0.86
4	6	4956	7207	10409	0.86
3	8	7864	1080	7699	0.86
4	9	4956	952	5098	0.86
1	9	4956	952	5098	0.86
7	9	6152	952	6178	0.87
3	6	7864	7207	13198	0.88
2	8	3335	1080	3898	0.88
7	8	6152	1080	6511	0.90
5	9	10084	952	9936	0.90
6	8	7207	1080	7598	0.92
4	5	4956	10084	13795	0.92
1	5	4956	10084	13795	0.92
6	9	7207	952	7553	0.93
2	5	3335	10084	12441	0.93
1	8	4956	1080	5604	0.93
4	8	4956	1080	5604	0.93
2	4	3335	4956	7796	0.94
1	2	4956	3335	7796	0.94
3	9	7864	952	8462	0.96
5	8	10084	1080	10783	0.97
1	4	4956	4956	9913	1.00

Table 5.2: In-sample MAPE's of the meters

Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1	288.88	17.76	9.61	8.62	37.50	8.36	14.84	12.43	7.33	8.00	10.05
2	34.24	21.72	10.57	14.69	49.44	8.52	17.13	7.46	78.67	33.37	34.06
3	12.12	7.25	12.16	20.09	16.13	8.16	18.21	5.44	15.28	18.78	10.12
4	205.81	13.18	9.61	8.62	35.25	9.20	14.84	11.75	7.33	8.00	10.05
5	10.15	5.05	7.50	10.30	5.84	5.82	10.08	5.37	10.41	44.23	9.86
6	9.57	7.40	8.42	16.24	21.50	8.00	13.33	7.68	9.52	11.16	357.53
7		774.49	8.69	8.01	12.85	6.48	14.07	7.28	11.45	8.68	12.15
8			603.99	325.60	577.27	160.43	671.83	527.53	666.75	477.74	970.46
9			76.71	610.35	157.80	415.50	162.40	1090.09	266.83	1468.50	427.02

To further confirm a load transfer, one may take a visual inspection by comparing the load profiles of the two meters. Figure 5.4 shows the top three meter-groups in Table 5.3, while the top two of them are also the top two groups in

Table 5.1. The load of Meter 9 has transferred completely to Meter 8, which has been ranked as the highest possible transfer by both proposed methods.

For the other groups of meters (other than top 3) in Table 4.1 and 4.3, since we cannot verify any load transfer via visual inspection, we consider them having no transfers. In this case, with 9 meters, the *MFM* ranked three existing load transfers as the 1st, 2nd and 14th potential pairs, while the *MBM* ranked them as first, second, and third pairs. In other words, if we just checked the three top-ranked pairs of meters in a visual inspection, we can detect two-thirds of the load transfers using BFM, and all of them using MBM.

Table 5.3: Meter groups sorted by MBI values

Meter$_i$	**Meter$_j$**	**MAPE$_i$**	**MAPE$_j$**	**MAPE$_{agg}$**	**Improved (Y/N)**	**MBI**
8	9	325.60	610.35	9.95	Y	0.00
3	5	20.09	10.30	4.87	Y	0.28
2	6	14.69	16.24	6.25	Y	0.33
2	9	14.69	610.35	10.29	Y	0.49
3	8	20.09	325.60	17.25	Y	0.74
6	8	16.24	325.60	14.59	Y	0.81
6	7	16.24	8.01	6.67	Y	0.86
2	7	14.69	8.01	6.64	Y	0.89
7	8	8.01	325.60	7.62	Y	0.91
1	6	8.62	16.24	7.26	Y	0.91
4	6	8.62	16.24	7.26	Y	0.91
2	8	14.69	325.60	14.10	Y	0.92
3	6	20.09	16.24	12.73	Y	1.02
1	2	8.62	14.69	7.52	Y	1.02
2	4	14.69	8.62	7.52	Y	1.02
7	9	8.01	610.35	8.13	N	1.03
2	3	14.69	20.09	12.17	Y	1.05
3	9	20.09	610.35	21.21	N	1.12
1	7	8.62	8.01	6.28	Y	1.14
4	7	8.62	8.01	6.28	Y	1.14
3	7	20.09	8.01	8.28	N	1.24
1	8	8.62	325.60	10.02	N	1.35
4	8	8.62	325.60	10.02	N	1.35
1	9	8.62	610.35	10.06	N	1.36
4	9	8.62	610.35	10.06	N	1.36
5	6	10.30	16.24	10.96	N	1.59
5	7	10.30	8.01	8.12	N	1.65
1	4	8.62	8.62	8.62	N	2.00
1	3	8.62	20.09	11.46	N	2.09
3	4	20.09	8.62	11.46	N	2.09
1	5	8.62	10.30	9.73	N	2.17
4	5	8.62	10.30	9.73	N	2.17
2	5	14.69	10.30	13.27	N	2.47
5	8	10.30	325.60	27.88	N	7.34
6	9	16.24	610.35	358.46	N	487.59
5	9	10.30	610.35	2930.68	N	80992.28

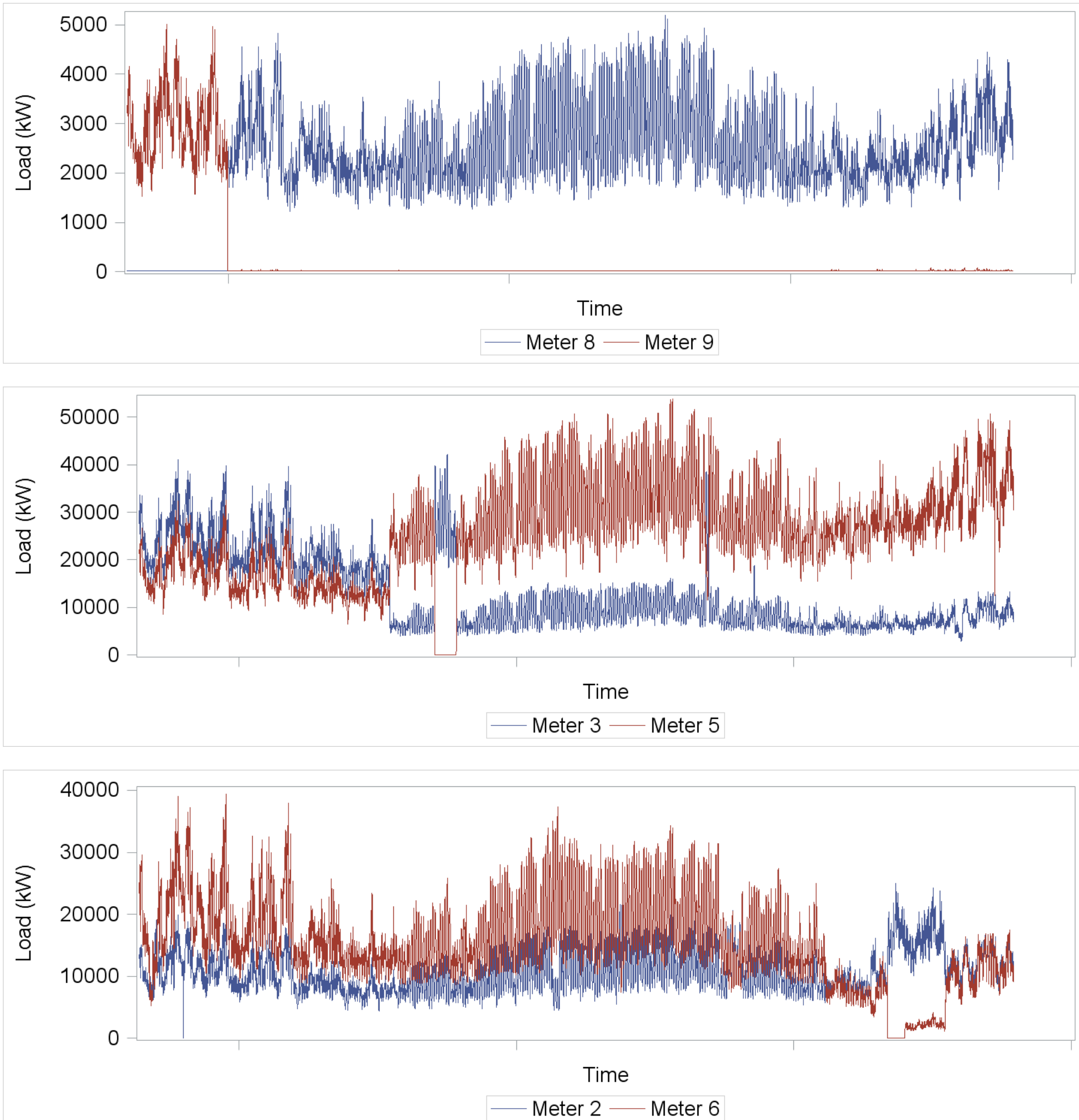

Figure 5.4: Load profiles of the top three meter groups (from top to bottom: 8 & 9; 3 & 5; 2 & 6).

B. Detecting simulated transfers

To further test the proposed methods, we simulate load transfers and inject them into the original load profiles of a load zone that does not transfer load among its delivery point meters. The simulation parameters are based on the characteristics of load transfers illustrated in Section 5.1 .

In simulating of the partial load transfers, it is not technically correct if we subtract, for instance, 80% of the hourly loads from a meter data and add it up to another meter, because we may ignore the randomness of load profiles. To model this arbitrary event, a random portion of each hourly load of the first meter is subtracted and then it is added to the corresponding hour of the other meter based on the following equation:

$$Load_t(i) = 0.01(k + rand)Load(i) \tag{5-4}$$

where $Load_t(i)$ is the transferred load between the meters, $Load(i)$ is the initial load of the first meter, k is the average portion of transferred load and $rand$ is a uniformly distributed random number between 0 and 1.

To implement the simulation framework on a domain we pick a load zone with no load transfers. The selected coop (COOP 21) includes 22 meters with full years (2006 to 2016) of hourly data. Based on the following factors we create virtual load transfers in different years to build a domain for the performance analysis.

- N: total number of load transfers
- n_K: number of load transfers in each year (1 in 60% of years, 2 in 30%, more than 3 in 10% of years)
- SD_s: The month of the starting point (50% in Mar, Apr and Oct)
- L_i: Length of each temporary load transfer. A random number following a log normal distribution, *log-normal(μ,σ)*

In addition, we have:

$$N = \sum_{k=1}^{T} n_k \tag{5-5}$$

where T is the total number of years in history data (here T is 11).

After preparing the domain, we apply the proposed methodologies to detect the virtual load transfers. We repeat the simulation and detection procedure for 100 times. In each iteration, the simulation parameters are allocated by assigning random numbers based on the criteria that we explained above. In total, we created 1700 virtual load transfers and injected them into the sample domain.

Figure 5.5 illustrates the performance of two methodologies in detecting the simulated load transfers. The graph shows the percent of the load transfers being detected as the top x pairs. If we take the top 10 groups ranked by two methodologies, 72% of the load transfers are detected by MBM, while 62% by the MFM. Overall, MBM outperforms MFM.

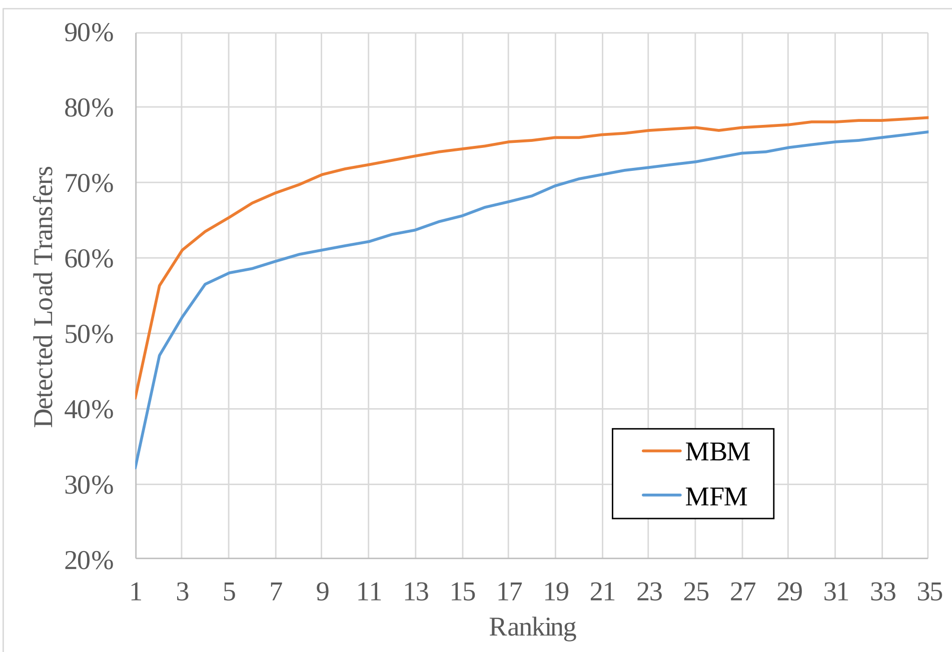

Figure 5.5: Percentage of the detected load transfers in top ranked pairs

5.4 Discussion

5.4.1 A Greedy Algorithm

For both methods, we rank the meter pairs to find high potential candidates. The simulation study in Section 5.3 showed that if we checked the top 10 pairs for this specific load zone, on average, we could detect 72% of the load transfers by the MBM and 60% of them by the MFM. On the other hand, we might detect additional load transfers if we move the screening bar to the lower ranks, which would result in a higher false positive rate and additional labor costs from more visual inspections. To address this challenge, we propose a greedy algorithm to further narrow down the potential candidates and consequently reduce the false positive errors. The greedy algorithm filters the ranked pairs by prioritizing the higher-ranked meter pairs. For example, if the top-ranked group includes $meter_i$ and $meter_j$, we filter any other groups with either one of these two meters until exhausting all groups. The algorithm process is explained in Algorithm 1.

Algorithm 1**:** The greedy algorithm

Input: $M = \{meter_i\ ,\ i=1,\ 2,\ \ldots,\ n\}$
$P = \{p_{i,j}\} = \{(meter_i,\ meter_j), meter_{i,j} \in M\ \}$
Calculate $MFI_{i,j}\ for\ p_{i,j} \in P$
Sort $MFI_{\text{i,j}}$ in ascending order
Rank $p_{i,j}$ based on $MFI_{i,j}$ position: $p_{i,j}^{r}, r = 1, 2, 3, \ldots$
for $p_{i,j} \in P$ **do**
  if $\left[(p_{i1,j1}^{r1} \cap p_{i2,j2}^{r2}) \neq \emptyset\ and\ r1 > r2\right]$ **then**
    $remove\ p_{i1,j1}^{r1}$
  end if
end for
Return the list of filtered $p_{i,j}$

If we filter the pairs ranked by the model-free method in

Table 5.1, the greedy algorithm narrows down 36 meter groups to five. Two of the three confirmed load transfers are in this shortlist of five. In Table 5.3, the greedy algorithm finds a shortlist of four, which includes all three load transfers. In other words, by integrating the greedy algorithm, we significantly reduce the pairs that require visual inspection and the false positive errors. Nevertheless, it might increase the false negative errors, because some load transfers may not be included in the shortlist. To quantify the impact of the greedy algorithm on the performance of the proposed methodology, we use two measurements, False Negative Rate (FNR) and False Positive Rate (FPR). FNR is the ratio of undetected to all load transfers, while FPR is the ratio of normal pairs detected as the load transfers to all normal pairs (pairs with no load transfer).

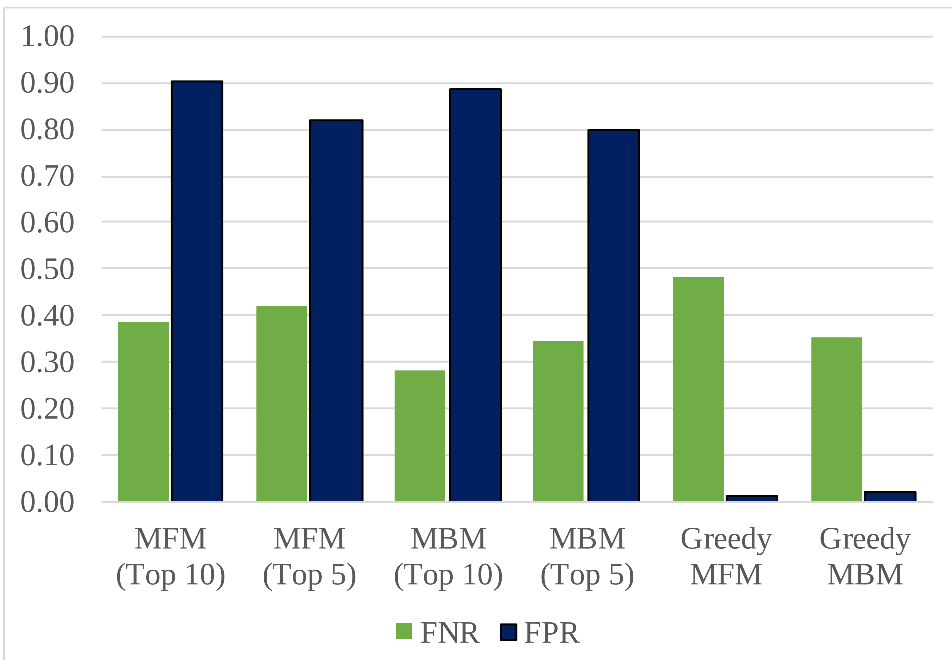

Figure 5.6: FNR and FPR of two methodologies in detecting simulated load transfers

Figure 5.6 compares the FNR and FPR for six different methodologies; MFM and MBM by taking top 5 and top 10 pairs, and MFM and MBM integrated with the greedy algorithm. The results show that the greedy algorithm decreased the false positive errors significantly but only increase the false negative slightly.

5.4.2 Transfers Among Multiple Meters

In the data, we did not find any load transfers among more than three delivery points. Therefore, in our experiments, we assumed that the load transfers always happen between only two meters. In reality, load transfers may occur among more than two meters sometimes. Detecting the load transfers among several meters can be done utilizing a similar idea. Instead of grouping two meters, we could group more than two meters and then investigate the aggregated load profiles. The proposed indices (MFI and MBI) could be extended to three or more components. Nevertheless, considering larger number of meters in a group would increase the computational costs of the implementation.

CHAPTER 6: GROUPING THE METERS

In chapter 5, we proposed a methodology for detecting load transfers. Knowing the meters with load transfers, the next step must be a solution to fix them in order to improve the data quality. We showed that a load transfer happens typically between two or more meters. The statistics of all detected load transfers in the whole dataset reveal the fact that a load transfer does not occur between a pair of random meters. The transfer typically occurs inside the group of given meters. This is also confirmed by the arrangements in the real operations. Transmission operators make a pair or a group of substations tied together and the load could transfer only between these tied substations.

Inspired by this fact, in this chapter, we propose a solution to fix the data quality issues caused by load transfers. This solution is a perquisite to the further improvement of the load data quality. It also is a fundamental requirement for the load forecasting at the delivery point level.

6.1 Methodology

A load transfer makes the shape of the corresponding load profiles abnormal. These damaged load time series are not appropriate to use in a load forecasting model. Removing or re-estimating the anomalies of a dataset are two typical approaches to fix the data quality issues. These methods are useful when the frequency of anomalies is reasonably low. The characteristics of the load transfers showed that a transfer could last from a few hours to even months. Therefore, removing or replacing the affected observations are not practical approaches.

The analysis of the load transfers in the case study demonstrates that the operators do not transfer load between two (or more) random meters. There are specific pairs (or groups) of meters that are tied together and the load could be transferred between them. Inspired by this finding, we propose a solution in order to improve the data quality issues for the meters with a load transfer.

The first step is to detect all load transfers in the historical data. This determines the pairs and groups of meters with load transfers. By detecting the “transfer groups”, we create virtual aggregation points in the hierarchy in which the meters of a given group are added together. The new virtual delivery points offset the load transfer and the aggregated load is expected to be like a normal profile.

To test the idea of grouping the meters, we compare the performance of a load forecasting practice in two approaches: with or without grouping. Assume that we have a group of (two or more) meters with load transfers and we want to forecast the load at one level higher in the load hierarchy. Without the information about the load transfer, one can use the forecasts by the individual meters to calculate the total forecast for the upper level. In the proposed methodology, we group the meters with load transfers. Therefore, in this approach, we first aggregate the loads of the meters that we already knew they have load transfers. Then, we use the aggregated load to generate the forecast for the upper level.

Figure 6.1 shows schematic diagrams of two different approaches. In the case study, we will compare the forecast accuracies by the two mentioned methods. Tao’s Vanilla Model (eq. 5-2) is used as the forecasting model for both methods and MAPE is the metric for error measurement.

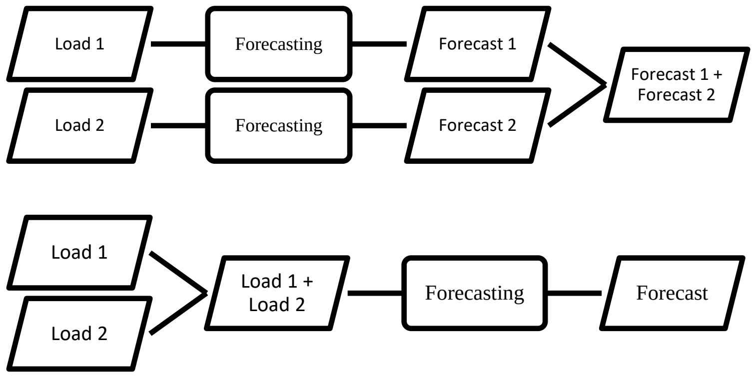

Figure 6.1: Two forecasting approaches for a pair of meters; top: approach 1, bottom: approach 2

6.2 Experiments

Similar to section 5.3 , we use Zone 9 to illustrate the proposed methodology. This zone has nine operating meters in the timeframe between 2014 and 2016. To show the load transfer history of these meters, we go back more years. This history defines the load transfer groups. By detecting the groups, in the next step, we test the grouping idea by comparing two forecasting approaches explained in the previous section.

Table 6.2 compares the forecast accuracies for the meter groups of the Zone 9 using two aforementioned approaches. In this forecasting, two years of data (2014 and 2015) are used to forecast 2016. For each meter, the weather stations are ranked based on the in-sample error in the training period. The weather station with the lowest error is selected as the best one. In the approach two, we aggregate the load first and then do the forecasting for the total load. In this case, the average temperature profiles are used in the model.

As we can see, grouping the meters with a load transfer improves the forecast accuracy significantly for two groups and has a marginal drop for one of them. For the group with almost no change (group [9.3, 9.5]), similar load transfers happened in every

two years of the training period. Since the transfers were in the exact time, in a regression model, they cancel each other. Therefore, the grouping does not make a considerable difference in the forecast accuracy. Overall, the proposed solution for the meters with a load transfer improves the data quality and prepares them for a load forecasting process.

Table 6.1 shows the detected load transfers between the meters of Zone 9. From 2013 to 2016, 10 distinct transfers were found on a yearly basis. These transfers belong to three groups of meters. In other words, the transfers only happen between the meters of three different groups. The groups are [9.1, 9.2, 9.6], [9.8, 9.9] and [9.3, 9.5].

Table 6.2 compares the forecast accuracies for the meter groups of the Zone 9 using two aforementioned approaches. In this forecasting, two years of data (2014 and 2015) are used to forecast 2016. For each meter, the weather stations are ranked based on the in-sample error in the training period. The weather station with the lowest error is selected as the best one. In the approach two, we aggregate the load first and then do the forecasting for the total load. In this case, the average temperature profiles are used in the model.

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Table 6.1: The load transfers in the Zone 9 from 2013 to 2016.

Zone	Year	$Meter_i$	$Meter_j$	Group
9	2013	9.1	9.6	Group 1
9	2013	9.8	9.9	Group 2
9	2014	9.3	9.5	Group 3
9	2014	9.8	9.9	Group 2
9	2015	9.3	9.5	Group 3
9	2015	9.2	9.6	Group 1
9	2015	9.8	9.9	Group 2
9	2016	9.2	9.6	Group 1
9	2016	9.1	9.6	Group 1
9	2016	9.8	9.9	Group 2

Table 6.2: Comparing the forecast accuracies using two methods

	MAPE (%)	
Meter Group	Without Grouping	With Grouping
9.1, 9.2, 9.6	20.13%	9.36%
9.8, 9.9	11.32%	9.99%
9.3, 9.5	13.00%	13.01%

6.3 Discussion

The results showed in the previous section demonstrate the benefits of the proposed solution. Grouping the meters with load transfers improves the data quality noticeably, in which we can have a significant enhancement in the forecast accuracies. In a normal situation, where two load profiles have no serious data quality issues like a load transfer, combining them could have either a good, bad or a neutral impact on the data quality. Even if combining two normal load profiles leads to a better performance in a load forecasting, the improvement is expected to be marginal (

Table 6.3). On the other hand, the results showed that combining the meters with a load transfer improved the data quality noticeably.

Table 6.3: Comparison between two forecasting approaches using normal meters with no load transfers

Group	Approach 1	Approach 2
[8.3, 8.4]	7.98%	7.87%
[17.1, 17.2]	9.38%	9.38%
[17.3, 17.4]	9.27%	9.30%
[20.3, 20.4]	6.56%	6.56%
[2.1, 2.4]	10.61%	10.36%

CHAPTER 7: OTHER LOAD ANOMALIES

In chapter 5, we showed that the major data quality issues in the load data at the distribution level are caused by load transfers. Nevertheless, there are other types of quality issues in the load data such as power outages and missing data. An outage is typically a local event. Falling of a tree, contact of a squirrel, lightning, or equipment failure can cause temporary and typically short outages in one or a few neighborhoods. These outages usually occur in limited areas of the service zone and are reflected in the reading of meters at one or a few substations. Therefore, at distribution level the frequency of outages are respectively high. An outage creates a gap with low or zero values in the load profiles. The resulted anomalies reduce the data quality and need to be addressed in load data analysis such as load forecasting. Missing data is another source of issues in the load data that typically caused by human error or failure in a meter.

In this chapter, we propose a methodology to detect the quality issues in the load data other than load transfers. The methodology is an additional step to the load transfer detection in order to screen all anomalies in the load data at the distribution level. The proposed idea is tested in a load forecasting practice in order to validate the improvement in the load data quality.

7.1 Methodology

In this section, we propose a methodology to detect the anomalies in the load data. It should be considered that the load transfer detection and grouping the meters are two primary steps before implementing the load anomaly detection and cleansing. In other words, the meters with a load transfer are required to be detected by the proposed methods (Chapter 5) and then they should be fixed by the grouping methodology (Chapter 6). The load anomaly detection is the last step to screen the remaining outliers in the load data.

The anomaly detection is a model-based methodology. The method employs a regression model to estimate the loads for the historical observations. The observations with high residuals are flagged as anomalies. The detected anomalies are then removed in order to cleanse the data.

For this methodology, we need three components: a forecasting model, an error metric and a threshold. The model is the Vanilla model (eq. 5-2), which is similar to what we used for the model-based load transfer detection. For the error metric, we use simple error (eq. 3-4).

After we calculate the residuals for all observations in the historical data, we will have a distribution of errors. Since a regression model is used to estimate the expected load, the residuals must follow a normal distribution. In order to have a global threshold to screen the anomalies, the residual distribution is converted into a standard normal distribution by applying the following equation.

$$z_i = \frac{error_i - \mu_{error}}{\sigma_{error}} \tag{7-1}$$

where z is the z-score, μ_{error} and σ_{error} are the mean and the standard deviation of the residuals. The threshold is defined for the z-score values. We know that for a two-tail normal distribution, the z-score equals to 1.96 and less covers 95% of the data. Therefore, any number greater than 1.96 leads to screening the observations in the far tails of the residual distribution. The higher the value we assume for the threshold (α), the more conservative detection results we get. A flowchart for the proposed algorithm is shown in Figure 7.1.

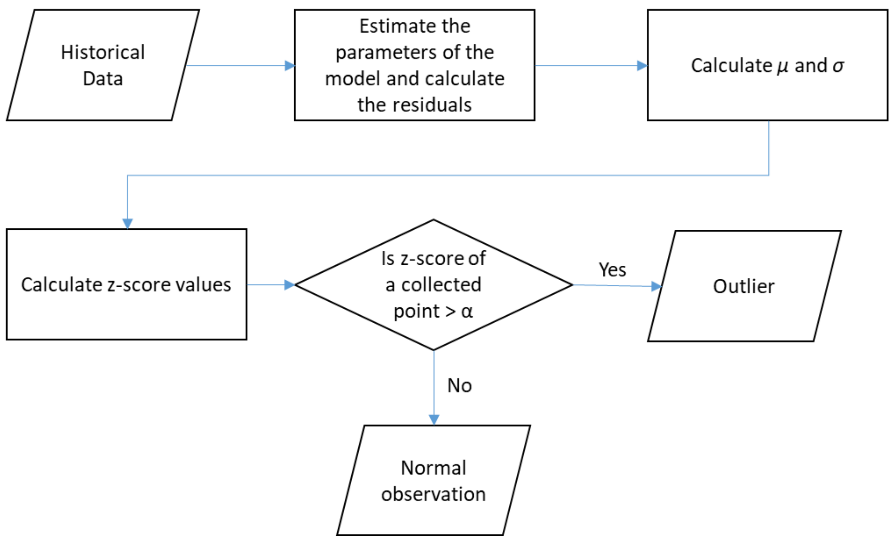

Figure 7.1: The flowchart of the anomaly detection algorithm

7.2 Experiments

The performance of the proposed methodology is evaluated through a load forecasting practice. The forecasting domain is similar to the previous chapters in order to see the improvement in every step of the data cleansing process. Therefore, two years of history (2014 and 2015) are used to train the Vanilla model and the forecasting horizon is the hourly loads of 2016. In this section, first, we test the anomaly detection methodology for a single meter (meter 7.6) which has no other data quality issues and then the method is implemented for the example zone (Zone 9).

After implementing the load transfer detection algorithm, no transfer was detected in the load history of the meter 7.6. Figure 7.2 illustrates the load profile of the meter for the year 2014. By visual inspection, we can see a long gap in the load data sometime in April 2014. Since we tested this meter in the load transfer process, this gap is not supposed to be due to a transfer. Therefore, a power outage can cause such a drop following with a long gap in a load profile.

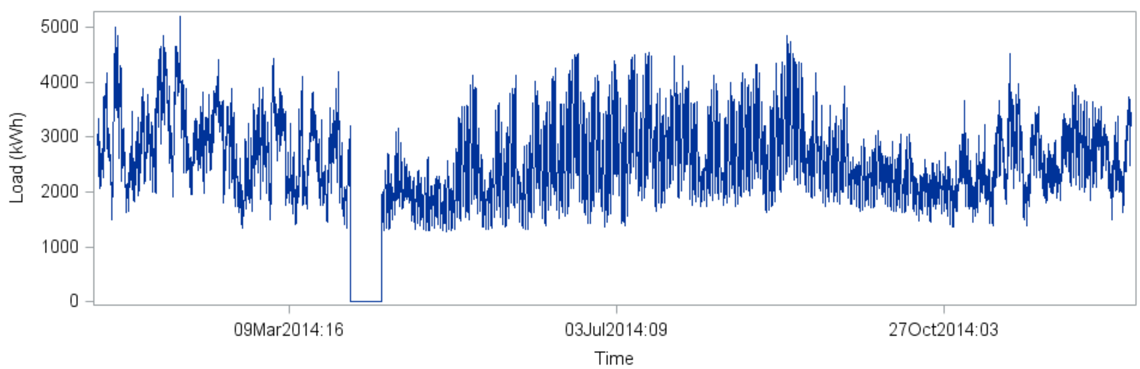

Figure 7.2: The hourly load profile of the meter 7.6 for the year 2014

We applied the proposed method for anomaly detection on two years of history. Then we removed the detected anomalies in order to cleanse the data. The raw data and cleansed data are used in separate load forecasting practices. For the cleansing, we tested the threshold value (α) from 2 to 10. The accuracy of load forecast using the raw and cleansed data are compared to each other in the final step in order to make a conclusion.

Figure 7.3 displays the histogram of the residual distribution. Obviously, most parts of the residuals are in the safe area, but a portion of them are located in the larger z-score zone. Table 7.1 depicts the forecasting results for the meter 7.6 including the forecast accuracies in MAPE and the number of detected anomalies in different levels of the detecting threshold. The results indicate that by removing the detected anomalies, at any level, the data quality improves which is quantified by the forecast accuracies.

On the other hand, the anomaly detection method has a different impact on the data quality at various threshold levels. Using a smaller value for the threshold leads to detecting more anomalies and as we move to the larger values, the number of anomalies decreases and consequently the forecast accuracy increases. The most accurate forecast is generated by screening the data and removing the detected anomalies with the threshold value equals three. Although alpha equals two detects more anomalies (which is 482), the forecast MAPE is larger than alpha equals three. This is because of the fact that the proposed method similar to any other detection algorithm can have false negative and false positive errors. Using a smaller value for the threshold moves the screening bar closer to the center of the residual histogram and exclude more observations from the data. Therefore, we expect higher false positive errors using smaller values and on the other hand higher false negative errors by larger values for the threshold.

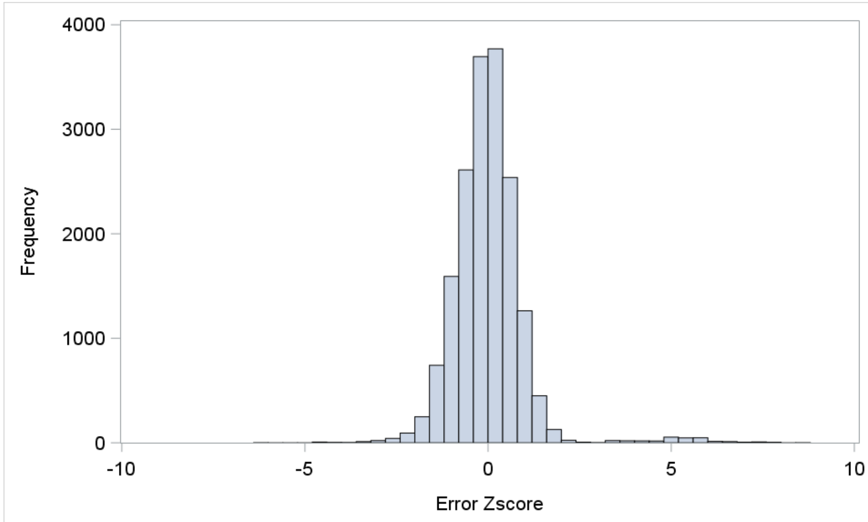

Figure 7.3: The residual distribution for the anomaly detection of the meter 7.6

Table 7.1: The accuracy of the forecasting in MAPE(%) using raw and cleansed data for the meter 7.6

	Raw	Cleansed								
Threshold (α)	-	2	3	4	5	6	7	8	9	10
MAPE	9.50%	7.18%	7.10%	7.32%	7.85%	9.06%	9.34%	9.49%	9.50%	9.50%
Anomalies Count	-	482	299	240	167	45	16	1	0	0

Furthermore, we test the proposed methodology on Zone 9 in order to monitor the improvement at each step of data cleansing. Table 7.2 shows the performance evaluation for the meter groups in Zone 9. In both single and group meters, we see improvement in the forecast accuracies after removing the detected anomalies.

Table 7.2: The forecast accuracy in MAPE(%) using the raw and the cleansed data for the Zone 9

Meter Group	Raw	2	3	4	5
9.1, 9.2, 9.6	9.06%	8.89%	8.93%	8.96%	9.03%
9.8, 9.9	9.99%	9.65%	9.81%	9.91%	9.98%
9.3, 9.5	13.01%	12.59%	12.80%	12.86%	12.94%
9.7	14.70%	13.91%	14.80%	14.73%	14.70%

The proposed anomaly detection method adds another layer of data cleansing to the load data at the delivery point level. Eventually, by following three steps of load transfer detection, grouping the meters, and anomaly detection, we take care of almost any possible data quality issues at the load profiles. The final product of this cleansing procedure is ready to be used in a load forecasting process.

CHAPTER 8: WEATHER DATA CLEANSING

The weather data used in load forecasting models are typically collected from the weather station instruments. The commercial weather companies serve the power utilities by providing more reliable reports than the public sources such as National Oceanic and Atmospheric Administration (NOAA). Although the private vendors improve the data quality through preprocessing phases to achieve the desired standard, the final products are not sufficiently prepared for a load forecasting process.

Weather variables are measured by point readings of the instruments located in the weather stations. Therefore, the data reflect the characteristics of a limited geographic area. On the other hand, the load data, at any level of the power grid hierarchy, is the aggregation of the end-users' load. Therefore, the electric load data come from the locations that are geographically spread across the service zone. The load profile of an end-user (a household) is affected by the weather conditions at the consumer's location. Therefore, using a single weather station to explain the variations of the load in a vast service zone is not enough. Hence, the load forecasters use the combination of multiple weather stations to have a better representation of the weather conditions in a large geographic area (Hong et al., 2015). In (Sobhani, Hong, Martin, 2019), the proposed methodology utilizes the best one load zone to cleanse the data of a weather station. Similar concerns are valid in the case of using one load zone to cleanse the temperature data.

In this chapter, we test the idea of using multiple load zones to cleanse the temperature time series for load forecasting. Three different approaches are proposed for treating multiple load zones in order to detect the anomalies of weather station data. The methods are compared with the benchmark introduced in (Sobhani, Hong, Martin, 2019).

8.1 Benchmark

We use the framework proposed in (Sobhani et al., 2020) as the benchmark. In this method, one load zone is used to cleanse the temperature data of a given weather station. The methodology utilizes a load-based temperature prediction model to detect the anomalies in the temperature time series. The temperature prediction model estimates the historical temperatures using the correlation between the temperature and load. The estimated values validate the actual ones and based on a predefined threshold, the anomalies are screened.

To implement the benchmark, four components are required including the temperature prediction model, the best load zone for a given weather station, error measurement and the threshold for the anomalies. The temperature prediction model is a piecewise regression function. Two regression functions are fitted to the corresponding legs of the temperature vs. load scatter plot (Figure 4.3). The cut-off point is set to the comfort temperature (here 61 ºF). To switch between the two models we group the history data by month and hour, which leads to 12×24 groups. For each group, we use the simple average temperature of that group as the cut-off. The regression model is formulated as follows:

$$\widehat{T_t} = \beta_0 + \beta_1 Trend_t + \beta_2 M_t + \beta_3 H_t + \beta_4 W_t + \beta_5 M_t H_t + \beta_6 W_t H_t + \beta_7 HLD_t + \beta_8 HLD_t M_t + \beta_9 HLD_t H_t + \sum_{i=-3}^{3} f(L_{t+i}, M_t, H_t) \quad (8\text{-}1)$$

and,

$$
\begin{aligned}
&f(L_t, M_t, H_t) \\
&= \beta_{10}L_t + \beta_{11}L_t^2 + \beta_{12}L_t^3 + \beta_{13}M_tL_t + \beta_{14}M_tL_t^2 + \beta_{15}M_tL_t^3 + \beta_{16}H_tL_t + \beta_{17}H_tL_t^2 \\
&+ \beta_{18}H_tL_t^3
\end{aligned}
$$

where $\widehat{T_t}$ is the temperature prediction for time *t*; β_i are the coefficients estimated using the ordinary least square method; M_t, W_t and H_t are the month-of-the-year, day-of-the-week, and hour-of-the-day for time t respectively, which are categorical variables; $L_t{+}i$ represents different levels of lagged and lead values for load and HLD_t is a classification variable representing the "big six" holidays of the U.S. including the New Year's Day, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, and Christmas Day.

The benchmark method uses one load zone to cleanse the temperature data. Therefore, for a given weather station we need to find the best load zone. Hence, the load zones are ranked based on the in-sample-error of the temperature predictions using the historical data. The pair of the weather station and the load zone with the lowest error is chosen. Mean Absolute Error (MAE) is used to measure the temperature prediction error (eq. 3-5).

After estimating the expected values for the temperatures, they are used to validate the actual observations. To detect the anomalies we use the in-sample errors of the temperature predictions. The residuals of a standard regression must follow a normal distribution. We convert it to a standard normal distribution, and then we mark the observations with the absolute value of the z-scores larger than a predefined threshold (α). The greater threshold we chose, the more conservative anomaly detection we haves. In other words, moving the threshold bar to the far tails of the standard normal distribution detects only extreme anomalies.

8.2 Methodology

The fundamental question of using multiple load zones to validate weather station data is that how we should treat multiple load zones for anomaly detection. Three approaches are proposed in this section to answer this question. In the first approach, which is called *Aggregation*, the total load of the zones are used as the input into the temperature prediction model. In the other two methods called *Intersection* and *Union*, the anomaly detection is conducted multiple times by using load zones individually. Intersect or union of the resulted sets of anomalies is then considered as the final list.

In all three methods, first we need to rank the load zones based on the correlation with the given weather station. Hence, the temperature prediction model introduced in Section 8.1 is trained with all pairs of the weather station and a load zone. The load zones are then ranked based on the in-sample errors with the lowest error having the top rank.

8.2.1 Aggregation

In this approach, the load zones are combined by aggregation. The aggregated loads of a number of zones are fed into the temperature prediction model. In other words, loads of top n zones are added up to calculate the total load for each timestamp. The temperature prediction model is then trained by the aggregated load data. As a result, the residuals of the regression model create a normal distribution where we can capture the anomalies similar to what the benchmark method does.

8.2.2 Intersection

Instead of combining multiple load zones, the temperature profiles of a weather station could be validated by each load zone separately. Therefore, the quality of weather data is being tested in multiple rounds. Given a number of load zones for a weather station, the final anomaly list of "Intersection" approach are the ones that have been confirmed by all load zones. We pair the weather data with every top *n* load zone and each pair is used to train the benchmark model. The output is *n* different sets of anomalies ($A_1, A_2, A_3, \dots, A_n$), which are not necessarily identical. Finally, we take the intersection set containing the members that belong to all anomaly sets.

$$A_{intersect} = \bigcap_{i=1}^{n} A_i \tag{8-2}$$

8.2.3 Union

The Intersection approach conservatively narrows down the anomalies to the ones with higher possibility. In the "Union" approach, we broaden the list of anomalies containing the observations that are validated by either one of the load zones. Therefore, given the sets of anomalies detected by individual load zones ($A_1, A_2, A_3, \dots, A_n$), the final list is the union set:

$$A_{union} = \bigcup_{i=1}^{n} A_i \tag{8-3}$$

8.3 Experiments

The quality of the input data affects the performance of a forecasting process reflecting in the forecast accuracy. We can measure the quality of the temperature data through a load forecasting practice. First, we input the raw data into a load forecasting model for an out-of-sample test and then calculate the forecast accuracy. In the next step, we detect the anomalies using the proposed methodologies and then cleanse the data by removing them. The same forecasting model is trained by the cleansed data and the accuracy of the corresponding forecast is calculated. By comparing the forecast accuracy before and after cleansing, we check the data quality improvement.

To implement the experiments we need three components including the load forecasting model, the appropriate weather station for a load zone and the error metric. The forecasting model is consistent with previous experiments. We use Vanilla model again for load forecasting (eq. 5-2). The best weather station for a given load zone is selected by ranking them in an out-of-sample test for a validation year. The weather station with the best forecast accuracy is chosen as the best station for the corresponding load zone. We use the Mean Absolute Percentage Error (MAPE) to measure the load forecast accuracy.

Four years (2013 to 2016) of hourly load and hourly temperature from 26 load zones and 28 weather stations are used in this experiment. To select the best weather station of a load zone, we use two years of 2013 and 2014 to forecast the validation year of 2015. For the data quality test, the training period is two years of 2014 and 2015 and forecast horizon is 2016. The weather station that is paired with each load zone goes through the data cleansing by the proposed methodologies. We check the load zones up to top10 to detect the anomalies of a weather station. The threshold for anomaly detection (α) is assumed three. In other words, the observation having the absolute z-score value greater than three is marked as an anomaly. This value excludes 1% from the tails of the distribution. A lower value increases the possibility of false positive errors and larger values make the screening more conservative with more false-negative errors

Table 8.1: The load forecasting MAPE (%) for the Aggregation method

			Number of load zones for temperature data cleansing									
Zone	WS	RAW	1	2	3	4	5	6	7	8	9	10
1	25	8.729	8.708	8.706	8.716	8.715	8.711	8.707	8.715	8.711	8.714	8.710
2	14	5.304	5.312	5.313	5.314	5.313	5.310	5.311	5.310	5.313	5.311	5.311
3	18	7.811	7.817	7.807	7.806	7.801	7.800	7.800	7.795	7.801	7.797	7.796
4	20	17.338	17.292	17.302	17.310	17.314	17.315	17.308	17.306	17.311	17.314	17.323
5	23	7.808	7.791	7.797	7.793	7.781	7.786	7.789	7.784	7.777	7.782	7.787
6	26	7.099	7.072	7.070	7.086	7.083	7.084	7.085	7.086	7.086	7.084	7.082
7	10	7.274	7.376	7.363	7.335	7.344	7.335	7.320	7.331	7.318	7.312	7.318
8	4	5.926	5.872	5.876	5.878	5.877	5.875	5.873	5.874	5.881	5.881	5.882
9	8	6.732	6.729	6.737	6.732	6.734	6.738	6.738	6.736	6.735	6.734	6.735
10	17	8.904	8.965	8.941	8.964	8.958	8.964	8.952	8.948	8.947	8.959	8.972
11	3	6.395	6.403	6.395	6.408	6.408	6.417	6.415	6.414	6.415	6.414	6.414
12	23	6.611	6.545	6.549	6.543	6.537	6.542	6.542	6.541	6.535	6.538	6.541
13	8	8.855	8.803	8.810	8.805	8.807	8.812	8.809	8.807	8.809	8.812	8.809
16	1	8.268	8.238	8.216	8.210	8.201	8.180	8.182	8.177	8.182	8.180	8.180
17	17	7.022	6.947	6.981	6.981	6.981	6.990	6.983	6.982	6.982	6.983	6.985
18	10	6.395	6.373	6.366	6.354	6.352	6.349	6.347	6.348	6.342	6.343	6.344
19	13	6.098	6.076	6.069	6.072	6.069	6.068	6.069	6.067	6.068	6.068	6.069
20	10	7.316	7.428	7.425	7.407	7.418	7.409	7.397	7.404	7.391	7.387	7.394
21	4	6.066	6.068	6.077	6.060	6.061	6.061	6.066	6.067	6.049	6.049	6.048
22	26	8.466	8.401	8.396	8.394	8.393	8.394	8.393	8.396	8.395	8.394	8.391
23	22	6.370	6.385	6.377	6.382	6.382	6.384	6.381	6.382	6.382	6.381	6.383
24	23	8.614	8.616	8.619	8.612	8.604	8.604	8.613	8.607	8.606	8.609	8.611
25	10	7.925	7.975	7.956	7.941	7.941	7.931	7.916	7.926	7.911	7.905	7.910
26	4	6.691	6.623	6.618	6.639	6.638	6.633	6.629	6.631	6.635	6.635	6.634
27	27	6.823	6.749	6.746	6.746	6.744	6.739	6.739	6.731	6.733	6.742	6.742
Average		7.634	7.623	7.620	7.620	7.618	7.617	7.615	7.615	7.613	7.613	7.615

Table 8.2: The load forecasting MAPE (%) for the Intersection method

			Number of load zones for temperature data cleansing									
Zone	WS	RAW	1	2	3	4	5	6	7	8	9	10
1	25	8.729	8.708	8.706	8.716	8.718	8.719	8.714	8.714	8.714	8.714	8.711
2	14	5.304	5.312	5.308	5.303	5.307	5.310	5.308	5.307	5.305	5.304	5.310
3	18	7.811	7.817	7.807	7.807	7.809	7.809	7.809	7.810	7.810	7.811	7.811
4	20	17.338	17.292	17.283	17.280	17.285	17.287	17.285	17.283	17.303	17.299	17.302
5	23	7.808	7.791	7.771	7.766	7.763	7.764	7.763	7.763	7.764	7.765	7.765
6	26	7.099	7.072	7.070	7.070	7.067	7.065	7.062	7.065	7.065	7.060	7.060
7	10	7.274	7.376	7.316	7.295	7.295	7.265	7.264	7.266	7.265	7.261	7.259
8	4	5.926	5.872	5.862	5.869	5.888	5.897	5.896	5.895	5.902	5.899	5.900
9	8	6.732	6.729	6.729	6.728	6.728	6.727	6.726	6.725	6.725	6.725	6.728
10	17	8.904	8.965	8.974	8.965	8.917	8.922	8.921	8.921	8.920	8.921	8.924
11	3	6.395	6.403	6.404	6.402	6.402	6.401	6.399	6.397	6.397	6.397	6.396
12	23	6.611	6.545	6.539	6.532	6.539	6.543	6.542	6.542	6.545	6.545	6.545
13	8	8.855	8.803	8.804	8.802	8.801	8.797	8.797	8.795	8.795	8.793	8.811
16	1	8.268	8.238	8.215	8.241	8.242	8.239	8.239	8.244	8.242	8.235	8.237
17	17	7.022	6.947	6.989	6.988	6.992	6.994	6.995	6.994	6.994	6.995	6.995
18	10	6.395	6.373	6.350	6.345	6.340	6.351	6.355	6.358	6.358	6.356	6.354
19	13	6.098	6.076	6.073	6.069	6.074	6.078	6.076	6.076	6.076	6.078	6.088
20	10	7.316	7.428	7.394	7.377	7.378	7.340	7.338	7.339	7.338	7.336	7.332
21	4	6.066	6.068	6.075	6.060	6.044	6.039	6.039	6.040	6.041	6.043	6.044
22	26	8.466	8.401	8.398	8.398	8.397	8.396	8.398	8.403	8.401	8.401	8.401
23	22	6.370	6.385	6.378	6.375	6.375	6.374	6.373	6.371	6.370	6.368	6.368
24	23	8.614	8.616	8.595	8.596	8.594	8.596	8.596	8.596	8.597	8.598	8.600
25	10	7.925	7.975	7.920	7.908	7.909	7.898	7.902	7.905	7.903	7.900	7.900
26	4	6.691	6.623	6.622	6.640	6.662	6.668	6.666	6.666	6.680	6.674	6.675
27	27	6.823	6.749	6.749	6.750	6.761	6.767	6.763	6.771	6.779	6.778	6.776
Average		7.634	7.623	7.613	7.611	7.611	7.610	7.609	7.610	7.612	7.610	7.612

Table 8.3: The load forecasting MAPE (%) for the Union method

			Number of load zones for temperature data cleansing									
Zone	WS	RAW	1	2	3	4	5	6	7	8	9	10
1	25	8.729	8.708	8.726	8.720	8.721	8.681	8.683	8.682	8.699	8.698	8.699
2	14	5.304	5.312	5.310	5.309	5.316	5.306	5.307	5.311	5.309	5.310	5.309
3	18	7.811	7.817	7.817	7.819	7.819	7.816	7.810	7.814	7.815	7.815	7.818
4	20	17.338	17.292	17.355	17.363	17.324	17.362	17.372	17.374	17.307	17.327	17.333
5	23	7.808	7.791	7.818	7.807	7.806	7.811	7.811	7.809	7.810	7.807	7.807
6	26	7.099	7.072	7.098	7.097	7.093	7.094	7.096	7.096	7.092	7.094	7.096
7	10	7.274	7.376	7.287	7.260	7.264	7.264	7.234	7.235	7.252	7.253	7.252
8	4	5.926	5.872	5.951	5.943	5.932	5.934	5.944	5.942	5.946	5.947	5.945
9	8	6.732	6.729	6.737	6.735	6.731	6.731	6.733	6.733	6.734	6.728	6.728
10	17	8.904	8.965	8.891	8.895	8.885	8.888	8.890	8.890	8.896	8.896	8.895
11	3	6.395	6.403	6.381	6.385	6.382	6.385	6.389	6.390	6.393	6.392	6.389
12	23	6.611	6.545	6.621	6.607	6.606	6.613	6.612	6.611	6.612	6.609	6.609
13	8	8.855	8.803	8.858	8.857	8.858	8.859	8.861	8.855	8.852	8.839	8.838
16	1	8.268	8.238	8.200	8.214	8.225	8.244	8.243	8.243	8.249	8.246	8.245
17	17	7.022	6.947	6.967	6.966	6.964	6.970	6.969	6.967	6.969	6.968	6.967
18	10	6.395	6.373	6.400	6.394	6.400	6.401	6.398	6.399	6.401	6.400	6.398
19	13	6.098	6.076	6.093	6.086	6.083	6.080	6.077	6.078	6.082	6.083	6.084
20	10	7.316	7.428	7.324	7.306	7.306	7.304	7.269	7.270	7.290	7.290	7.290
21	4	6.066	6.068	6.049	6.050	6.054	6.046	6.044	6.045	6.035	6.035	6.038
22	26	8.466	8.401	8.467	8.463	8.463	8.461	8.466	8.464	8.460	8.459	8.454
23	22	6.370	6.385	6.374	6.370	6.368	6.366	6.365	6.364	6.362	6.362	6.362
24	23	8.614	8.616	8.624	8.593	8.592	8.604	8.607	8.607	8.612	8.597	8.598
25	10	7.925	7.975	7.925	7.912	7.915	7.916	7.901	7.901	7.911	7.913	7.912
26	4	6.691	6.623	6.709	6.704	6.686	6.688	6.698	6.702	6.701	6.703	6.702
27	27	6.823	6.749	6.820	6.819	6.832	6.825	6.821	6.820	6.821	6.822	6.832
Average		7.634	7.623	7.632	7.627	7.625	7.626	7.624	7.624	7.624	7.624	7.624

Table 8.1, Table 8.2 and Table 8.3 depict the results of the quality tests for the Aggregation, Intersect and Union methods respectively. Each table is a heat map with cooler color (green) indicating lower MAPE, and warmer color (red) indicating higher

MAPE. The "RAW" column means that the raw temperature data is used in the load forecasting with no primary cleansing.

By the Aggregation method, in 60% of cases, using multiple load zones to cleanse the weather data generate the lowest MAPE, in 20%, using one zone resulted in the best MAPE and in the remaining, the data quality did not improve. In the Intersect method, cleansing by multiple load zone wins in 80% of the cases, single load zone wins in 8% and in the remaining, the forecast accuracy did not improve. In the Union method, single and multiple load zones tie and only in one case, the forecast accuracy does not improve. On average, using eight zones in the Aggregation method and six zones in the Intersect method produce the lowest MAPE, but using multiple load zone with Union method does not improve the data quality.

8.4 Discussion

The results demonstrate that using multiple load zones to cleanse the weather data performs better in most cases. It is because of that the variations of the temperature data cannot be explained completely by using only one load zone. Due to geographical reasons, the correlation between temperature data collected from a weather station, and various load zones is different. Therefore, using multiple load zones provides the opportunity of taking advantage of these diverse correlations to validate the temperature data. Among the three proposed methods, Intersect produces the most desirable results. The main reason is the conservative nature of this method. Using Intersect, we only take the observations that are confirmed by all quality tests. In other words, if only one load zone does not approve the anomalous behavior of a temperature reading, we will keep that observation. That makes the Intersect method more likely to have lower false positive errors. On the other hand, the Union has the worst results on average, because the method tries to cover any possible anomalous observation. Therefore, the Union method raises the cost by increasing the false positive errors in order to achieve a lower false negative error. However, the benefit of the Union method is in the cases where the other two methods cannot improve the data quality but this method was able to do that.

CHAPTER 9: DELIVERY POINT LEVEL FORECASTING

In the previous chapters, we studied different challenges in load forecasting at the delivery point level. The focus of this research is mainly on analyzing the data quality issues in both load and weather data, which are two major sources of input in an electric load forecasting model. The dataset used in this research includes the load data from hundreds of delivery points and weather data from a number of stations across the service territory. Up to this point, we took one of the load zones in order to elaborate on the proposed methodologies and their performances. In this chapter, we summarize the final framework for load forecasting at the delivery point level and then test the framework for all zones and meters in the dataset in order to demonstrate the effectiveness of the proposed solution.

9.1 Framework

The final solution for load forecasting at the delivery point level is a framework, which consists of different components. The framework tackles the expected challenges in a load forecasting practice at the delivery point through different components. The components include load transfer detection, grouping the meters, load anomaly detection, and weather data cleansing. The responsibility of all these solutions is to improve the data quality for both load and temperature. Therefore, we can divide the framework into two groups of components: load data quality improvement and weather data quality improvement. However, the forecasting model, which handles the randomness issue, kept consistent for the whole research because it is out of the scope.

Figure 9.1 illustrates the procedure for improving the quality of load data. The raw data of meters go through multiple layers of screening and quality enhancement. The final product is load time series that are ready to be inserted into the load forecasting model.

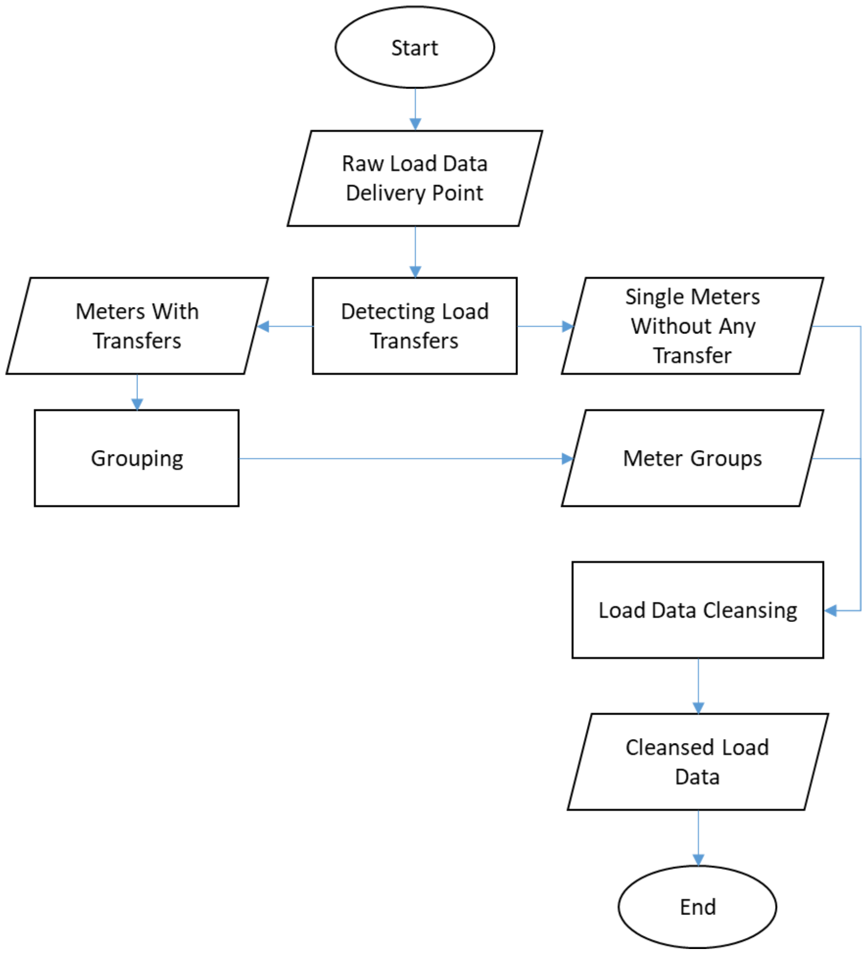

Figure 9.1: The flowchart for the process of improving load data quality

The second part of this framework is for the procedure to improve the weather data quality. Figure 9.2 shows the corresponding flowchart for cleansing the weather data. Therefore, both weather data and delivery point load data must go through these two procedures in order to prepare for the forecasting model.

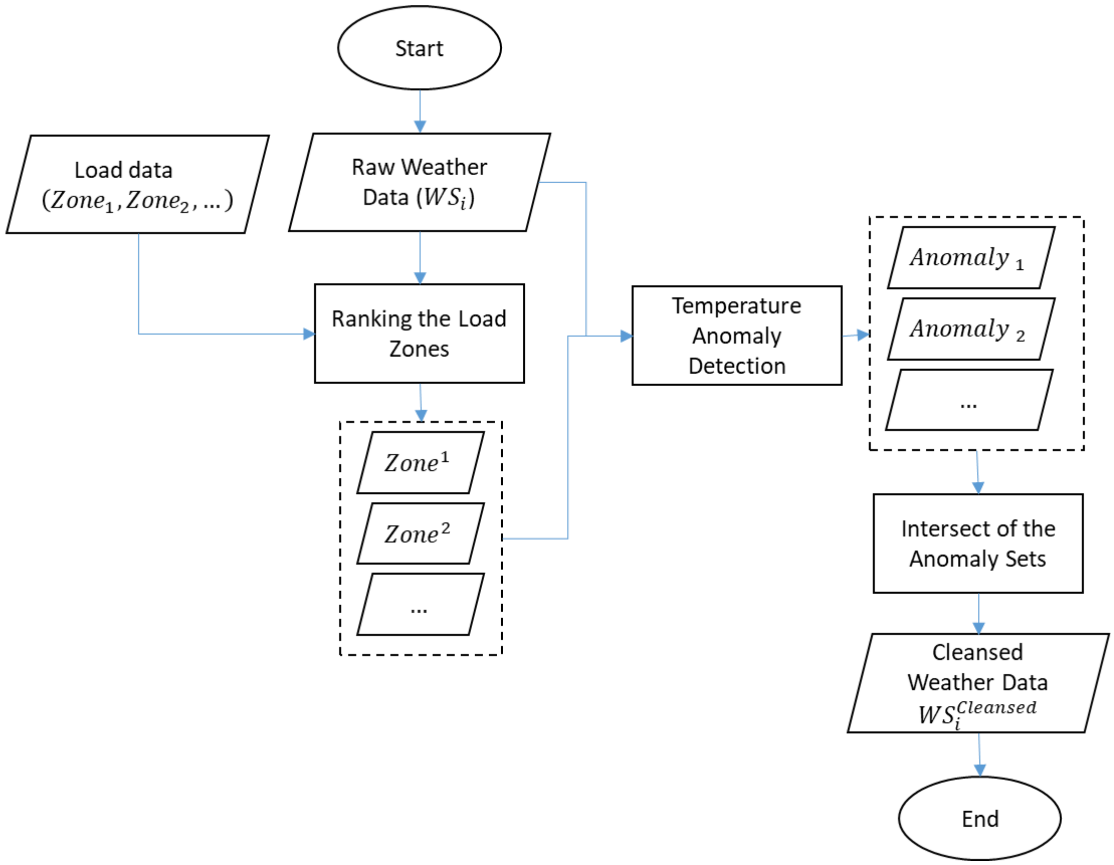

Figure 9.2: The flowchart for the process of improving weather data quality (Intersect method)

9.2 Results

This section presents the results of a comprehensive experiment using the whole dataset. We studied the performance of the proposed framework on all 26 load zones and corresponding delivery points. The load data is prepared using the flowchart shown in Figure 8.1 and the temperature is cleansed through the process explained in Figure 8.2. We used *Intersection* technique for weather data cleansing because of that the experiments in chapter 8 proved a better performance for *Intersection* method among three ones.

In this procedure, the very first step is to detect the load transfers between the meters in the historical data. In order to evaluate the performance of the proposed detection methods (Chapter 5), all meters were investigated manually by visual inspection. Therefore, we found all load transfers that look obvious through the visual inspection. In total, there are 177 load transferred in 11 years of data. The proposed methodologies (MFM and MBM) were successful to detect most of the transfers. The detailed results for the of the study of performances are shown in Appendix B.

Figure 9.3 compares the detection strength of the two methods. If we check the top 10 meters that are ranked by the methods, we are able to detect more than 75% of the transfers. In addition, the green bar shows the transfers that are detected by either one of the methods. The ratio of successful detection is significantly more than the individual ones. In other words, using both methods to detect load transfers is more effective than single ones. The performance results demonstrate that methods have different performance in different situations. For cases such as industrial load profiles where the model-based method cannot produce accurate load predictions, the model-free method is more effective and vice versa. The greedy algorithm also preforms reasonably good in detecting the load transfers. Seventy five percent of the transfers are detected by integrating the greedy algorithm into either one of the proposed methods.

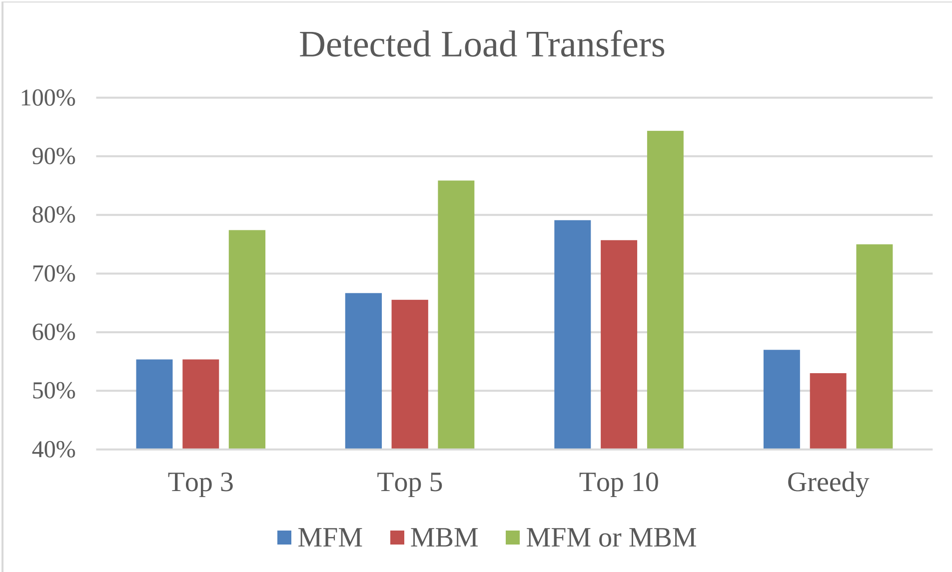

Figure 9.3: The ratio of detected load transfers using two methods

After detecting the load transfers, the meters are divided into two categories; single meters that are the ones with no load transfer in the history; groups of meters that are the sets of meters with load transfers. The groups of meters are required to be grouped first (Chapter 6) for load forecasting. The next step is similar for both single and groups which is load data cleansing (Chapter 7) and weather data cleansing (Chapter 8).

Similar to what we did using the sample Zone in the previous chapter, we evaluate the quality improvement by the proposed framework through a forecasting practice. Same forecasting model (Vanilla) and the error metric (MAPE) is used in this section. Two years of data (2014 and 2015) are used to forecast 2016. The forecast accuracy at each phase of the quality improvement procedure is measured.

Table 9.1 depicts the results for the forecasting of the meter groups. The accuracy of the forecasting in MAPE is shown for each step of the proposed framework. The table is a heat map where the lower values in green color and higher ones in red color. In total, 24 groups were detected among all of the delivery points. In 67% of the case, grouping the meters improved the forecast accuracy significantly, while in the other cases, the MAPE remains almost the same. The load data cleansing method enhances the forecast accuracy in 88% of the cases and in 75% cases the forecast accuracy after weather data cleansing wins. In overall, the proposed framework shows a successful performance for the meter groups.

Table 9.1: The load forecasting results in MAPE (%) for the meter groups

Group	Without Grouping	With Grouping	Clean Load	Clean Load + Weather
[2.3, 2.4]	5.25	5.25	5.17	5.18
[3.2, 3.4, 3.6, 3.8]	8.11	7.33	7.27	7.25
[5.2, 5.6, 5.13]	19.44	7.53	7.44	7.44
[6.9, 6.10]	17.71	17.71	17.58	17.50
[6.11, 6.12]	15.40	15.44	15.50	15.47
[8.15, 8.32]	9.30	9.30	9.42	9.40
[9.1, 9.2, 9.6]	20.13	9.36	9.38	9.38
[9.3, 9.5]	13.00	13.01	12.80	12.79
[9.8, 9.9]	11.32	9.99	9.81	9.82
[13.8, 13.21]	328.03	18.86	18.60	18.54
[13.9, 13.22]	50.32	9.67	9.34	9.32
[13.12, 13.23]	32.91	10.05	9.92	9.89
[16.17, 16.18]	9.60	8.60	8.46	8.49
[16.19, 16.20]	7.28	7.27	7.23	7.19
[17.10, 17.13]	114.69	9.58	9.46	9.46
[17.12, 17.14]	6158.52	20.71	20.52	20.49
[18.3, 18.5, 18.8]	45.86	6.41	6.38	6.38
[20.2, 20.9]	10.44	10.42	10.39	10.33
[22.13, 22.15]	10.22	10.22	10.21	10.12
[24.1, 24.2]	14.90	14.90	14.76	14.76
[24.7, 24.8]	10.00	8.89	8.77	8.77
[26.10, 26.11, 26.13]	14.63	8.04	8.02	8.02
[27.1, 27.15]	7.40	7.15	7.10	7.07
[27.8, 27.17]	180.43	7.69	7.63	7.59

The load transfer detection procedure screened 286 meters without any transfers. Appendix B presents the detailed results of the load forecasting test for the single meters.

The forecast accuracy is calculated using three sets of data: raw load and raw weather data, cleansed load and raw weather data, and cleansed load and cleansed weather data. In 69% of the single meters, using cleansed weather and cleansed load data produced the most accurate forecasts, in 20% of the cases, using cleansed load and raw weather data wins and in the remaining (11%) using the raw data for both load and weather have the lowest MAPE.

For a visual perspective, Figure 9.4 and Figure 9.5 compare the load forecasts for the group of the meters [9.1, 9.2, and 9.6] with the actual load profile in a sample week and day respectively. The line plots are for the forecasts using the data with different levels of quality improvement. As we can see, the forecast with no grouping as the most offset from the actual values. After grouping, the forecasts are very close to each other and the improvement is respectively marginal.

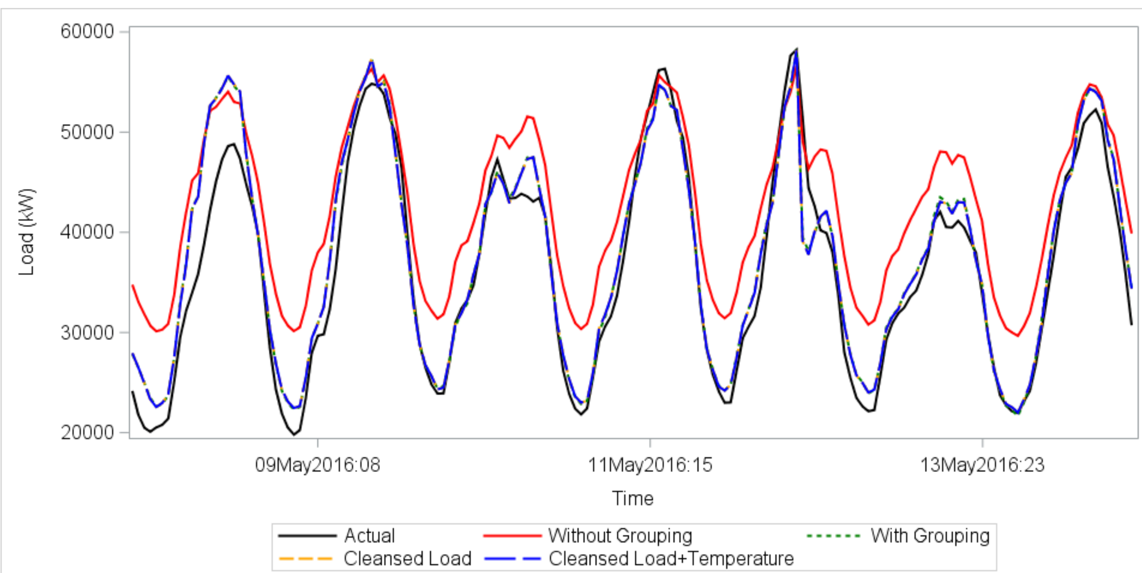

Figure 9.4: Comparison of the load forecasts in a sample week, using the data with different levels of the quality improvement for the group meter (9.1, 9.2, 9,6)

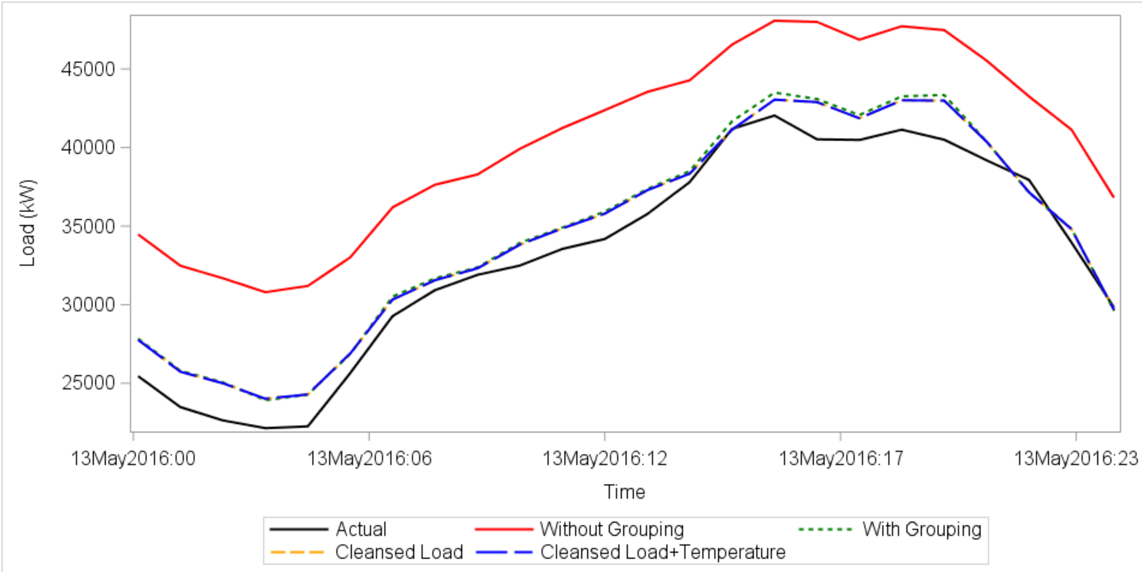

Figure 9.5: Comparison of the load forecasts in a sample day, using the data with different levels of the quality improvement for the group meter (9.1, 9.2, 9,6)

9.3 Discussion

The results of the comprehensive experiment for all 428 meters demonstrate the effectiveness of the proposed methodology. The improvements are sometime significant but sometimes marginal. The intensity of the data quality issues in different situations determines the level of improvements.

There are some arguments we can have for the proposed framework. The quality improvement started with the load data. Both procedures for cleansing load and weather data are done separately. In other words, we use raw weather data in load part of framework and vice versa. Therefore, the quality of raw weather data, for instance, can affect the performance of load data cleansing. The major question is that should we do it separately or together. This raises the second question. Which one should be improved first? An alternative approach could be multiple rounds of cleansing.

In all forecasting practices we have done in this research, for a given load data we only used one weather station. In the introduction and literature review we mentioned that a single weather station is not always enough to explain the variation of load. If we use multiple weather stations in the forecasting process, the cleansing becomes way more complicated.

Although this research do not have particular answer for mentioned arguments, the purpose of this dissertation is to build a foundation for delivery point load forecasting. All these arguments could be investigated through the framework proposed in this research.

CHAPTER 10: CONCLUSION

Electric load forecasting is a basic requirement for every sector of the power industry. The power utilities use short-term and long-term load forecasts at the system level to plan their operations while the electricity retailers use load forecasts at the end-user level for pricing and procurement decisions. In a power delivery network, delivery points are the nodes where the electricity is delivered to the distribution lines in order to supply power for a limited area. The load forecasting at the delivery point level provides values to power utilities and distribution operators. More accurate forecasts at lower levels of a power hierarchy could improve the system load forecast accuracy, which leads to better planning and operations. For load management tasks, accurate load forecasts at substation level help operators and decision-makers to prevent some unexpected events such as outages, congestion and equipment overloading.

Forecasting the load profiles at the delivery point level encounters two major challenges: data quality issues and randomness. The forecasting models are responsible to address randomness of load profiles. Data quality issues are related to the input data. The quality of data should be improved before they are used in a load forecasting model. The focus of this research is on data quality issues. The hypothesis is that by improving the quality of input data in a given forecasting model we expect an increase to the forecast accuracy.

Data quality issues at different levels of a load hierarchy are unique. Load transfers and outages are two major sources of quality issues in delivery point load data. Load transfer is a load management task for enhancing system reliability. Outages are reflected more in load profiles of lower levels of aggregation. On the other hand, the load is not the only data used in a load forecasting model. The correlation between the load and weather for the residential sector has been used in many load forecasting models. Similarly, real-world weather data contains anomalies and outliers.

In this research, we proposed a framework for delivery point load forecasting. The framework consists of different components tackling the data quality issues for both load and weather data. The performance of the proposed solution is evaluated through a case study using the data from a power utility in the United States.

Each component of the proposed framework addresses a specific problem and provides a solution. The components include detecting load transfers, grouping the meters, load data cleansing and weather data cleansing. For the load transfer detection, two novel methods are proposed and in the case study, they could detect 94% of the transfers. Grouping the meters improves the forecast accuracies in 67% of the cases. The proposed solution for load anomaly detection enhanced the data quality in 88% of the cases for the meter groups and in 81% of the single meters. For the weather data cleansing, a novel methodology was proposed where the load data from multiple load zones are used to validate the temperature data of a weather station. The results demonstrate that the proposed method is successful in 75% of meter groups and in 69% for the single meters.

This research proposed a novel solution for delivery point load forecasting. The aim was to fill the gap in the literature with a comprehensive study on the forecasting problem at the MV/LV level of the power hierarchy. We tried to build a foundation for a practical solution addressing the data quality issues in delivery point load forecasting. The effectiveness of the proposed framework was confirmed in a comprehensive case study using real-world data from a power utility in the United States.

This research opens a door for future extensions. There are plenty of rooms to improve each component of the framework. Some extensions to this study are listed as follows:

1. The methods for load transfer detection are designed for transfer between two meters. These methods can be leveraged for transfers between more than two meters.
2. The load transfer detection methods are more effective for longer transfers. By customizing the features of the methods, short and very short transfers could be screened for a more precise analysis.
3. The weather data cleansing procedure is developed for the quality improvement of the data from a single weather station. In many practices, multiple stations are combined for load forecasting. The optimal strategy for data cleansing of combined weather stations is another path for future research.
4. In the proposed load and weather data cleansing methods, predefined thresholds were used to screen the anomalies. Finding the optimum value for the thresholds could enhance the performance of the anomaly detection. In addition, using a customized threshold for different periods of time instead of fixed values could be studied in the future.
5. The procedure of data cleansing in the proposed framework starts with cleansing the load data and then the weather data. The quality of load data

affects the performance of weather data cleansing and vice versa. A procedure with multiple rounds of cleansing for both load and weather data can result in better outputs.

Appendix A: Data Availability and Simple Statistics for All Meters

Table A.1: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1	1.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.4	Yes	No	No	No	No	No	No	No	No	No	No
1	1.5	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
1	1.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
1	1.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
1	1.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.12	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1	1.13	No	No	No	Yes	No	No	No	No	No	No	No
1	1.14	No	No	No	No	No	No	No	No	No	Yes	Yes
1	1.15	No	No	No	No	No	No	No	No	No	No	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
2	2.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2	2.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2	2.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2	2.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2	2.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
3	3.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.7	Yes	Yes	Yes	No	No	No	No	No	No	No	No
3	3.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.9	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	3.10	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
3	3.11	No	No	No	No	No	No	No	No	No	No	Yes
3	3.12	No	No	No	No	No	No	No	No	No	No	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
4	4.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	4.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	4.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	4.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	4.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	4.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	4.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	4.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
5	5.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.13	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.14	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.15	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5	5.16	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
6	6.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
6	6.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.13	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.14	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	6.15	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
6	6.16	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
7	7.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
7	7.4	No	No	No	No	No	No	No	No	No	No	No
7	7.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
7	7.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.12	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	7.13	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
7	7.14	No	No	No	No	No	No	No	No	Yes	Yes	Yes
7	7.15	No	No	No	No	No	No	No	No	Yes	Yes	Yes
7	7.16	No	No	No	No	No	No	No	No	No	No	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
8	8.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.15	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.16	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.17	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.18	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.19	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.20	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
8	8.21	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.22	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.23	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.24	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.26	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.27	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.28	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.29	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.30	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.31	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.32	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.33	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.34	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.35	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.36	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.37	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.38	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.39	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.40	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.41	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.42	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.43	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.44	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	8.45	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
8	8.46	No	No	No	No	No	No	No	No	No	No	Yes
8	8.47	No	No	No	No	No	No	No	No	No	No	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
9	9.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.7	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.8	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.9	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	9.10	No	No	No	No	No	No	No	Yes	Yes	Yes	No
9	9.11	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
9	9.12	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
9	9.13	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
10	10.1	No	No	No	No	No	No	No	No	No	No	No
10	10.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.7	No	No	No	No	No	No	No	No	No	No	No
10	10.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.10	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.11	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.12	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	10.13	No	No	No	No	No	No	No	No	No	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
11	11.1	Yes	Yes	No	No	No	No	No	No	No	No	No
11	11.2	Yes	Yes	No	No	No	No	No	No	No	No	No

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
12	12.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.7	No	No	No	No	No	No	No	No	No	No	No
12	12.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.14	Yes	Yes	No	No	No	No	No	No	No	No	No
12	12.15	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	12.16	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
13	13.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
13	13.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.15	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.16	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.17	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.18	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
13	13.19	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
13	13.20	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
13	13.21	No	No	No	No	No	No	No	No	Yes	Yes	Yes
13	13.22	No	No	No	No	No	No	No	No	Yes	Yes	Yes
13	13.23	No	No	No	No	No	No	No	No	Yes	Yes	Yes
13	13.24	No	No	No	No	No	No	No	No	No	Yes	Yes
13	13.25	No	No	No	No	No	No	No	No	No	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
14	14.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.10	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
14	14.11	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
14	14.12	No	No	No	No	No	No	Yes	No	No	No	No
14	14.13	No	No	No	No	No	No	No	Yes	Yes	Yes	No
14	14.14	No	No	No	No	No	No	No	No	No	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
15	15.1	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
15	15.2	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
15	15.3	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
15	15.4	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
15	15.5	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
16	16.1	No	No	No	No	No	No	No	No	No	No	No
16	16.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.4	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
16	16.5	No	No	No	No	No	No	No	No	No	No	No
16	16.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.13	No	No	No	No	No	No	No	No	No	No	No
16	16.14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.15	No	No	No	No	No	No	No	No	No	No	No
16	16.16	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
16	16.17	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.18	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.19	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.20	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
16	16.21	No	No	No	No	No	No	No	Yes	Yes	Yes	No
16	16.22	No	No	No	No	No	No	No	No	Yes	Yes	No
16	16.23	No	No	No	No	No	No	No	No	No	Yes	Yes
16	16.24	No	No	No	No	No	No	No	No	No	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
17	17.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.5	Yes	No	No	No	No	No	No	No	No	No	No
17	17.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.11	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
17	17.12	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
17	17.13	No	No	No	No	No	No	No	No	No	Yes	Yes
17	17.14	No	No	No	No	No	No	No	No	No	No	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
18	18.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
18	18.2	Yes	Yes	Yes	No	No	No	No	No	No	No	No
18	18.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
18	18.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
18	18.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
18	18.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
18	18.7	Yes	Yes	Yes	No	No	No	No	No	No	No	No
18	18.8	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
18	18.9	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
18	18.10	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
19	19.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
19	19.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
19	19.15	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
19	19.16	No	No	No	No	No	No	No	Yes	Yes	Yes	No
19	19.17	No	No	No	No	No	No	No	No	Yes	Yes	No
19	19.18	No	No	No	No	No	No	No	No	No	No	Yes
19	19.19	No	No	No	No	No	No	No	No	No	No	Yes
19	19.20	No	No	No	No	No	No	No	No	No	No	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
20	20.1	No	No	No	No	No	No	No	No	No	No	No
20	20.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.14	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
20	20.15	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
21	21.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.15	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.16	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.17	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.18	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.19	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.20	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.21	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
21	21.22	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
22	22.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.3	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
22	22.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.9	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
22	22.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.15	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.16	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.17	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.18	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.19	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.20	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.21	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
22	22.22	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.23	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
22	22.24	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
22	22.25	No	No	No	No	No	No	No	Yes	Yes	Yes	No
22	22.26	No	No	No	No	No	No	No	No	No	Yes	Yes

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
23	23.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
23	23.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
23	23.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
23	23.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
23	23.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
23	23.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
23	23.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
23	23.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
23	23.9	Yes	Yes	No	No	No	No	No	No	No	No	No

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
24	24.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
24	24.13	No	No	No	No	No	No	Yes	No	No	No	No
24	24.14	No	No	No	No	No	No	No	No	No	No	Yes
24	24.15	No	No	No	No	No	No	No	No	No	No	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
25	25.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25	25.14	No	No	No	No	Yes	No	No	No	No	No	No

Table A.1.cont: Data availability in different years for all zones and meters

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
26	26.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
26	26.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
26	26.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.4	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
26	26.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.12	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
26	26.13	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Zone	Meter Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
27	27.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.2	No	No	No	No	No	No	No	No	No	No	No
27	27.3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
27	27.8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
27	27.9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.10	No	No	No	No	No	No	No	No	No	No	No
27	27.11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.13	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.14	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
27	27.15	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
27	27.16	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
27	27.17	No	No	No	No	No	No	No	No	No	Yes	Yes
27	27.18	No	No	No	No	No	No	No	No	No	Yes	Yes

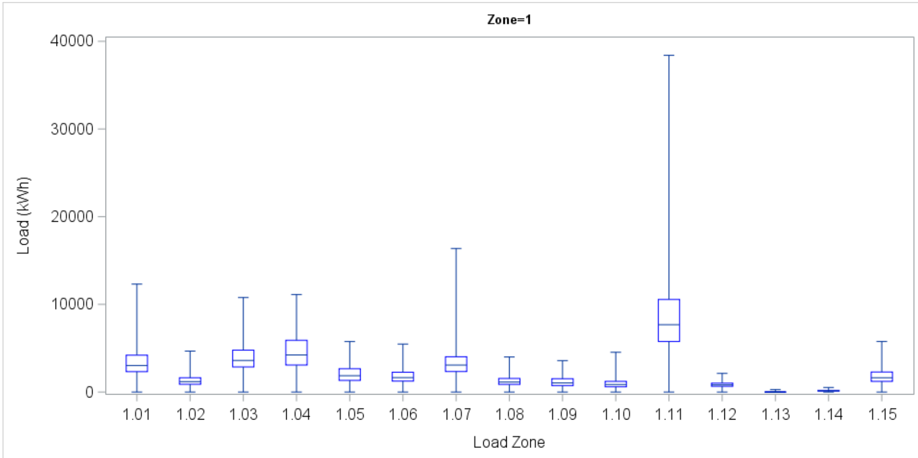

Figure A.1: Boxplot of the meter loads at Zone 1

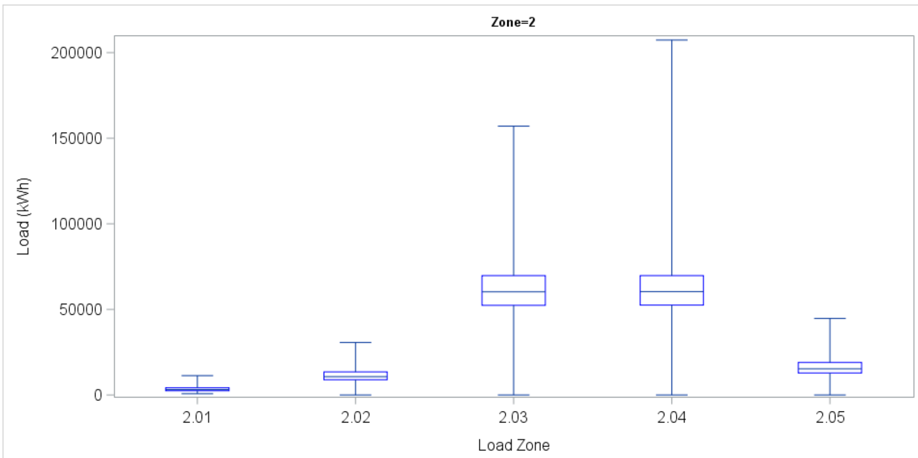

Figure A.2: Boxplot of the meter loads at Zone 2

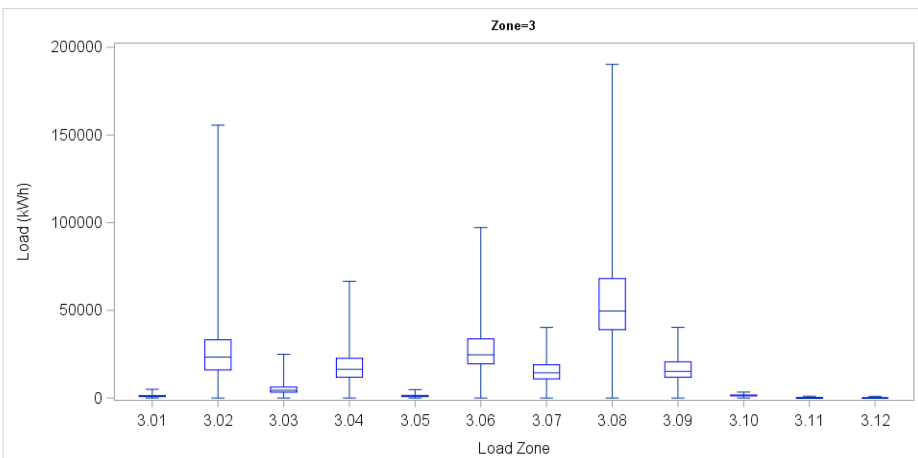

Figure A.3: Boxplot of the meter loads at Zone 3

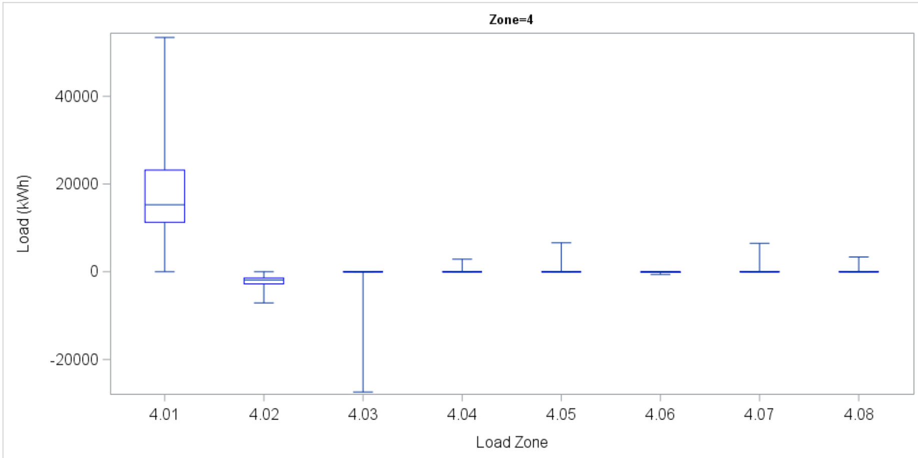

Figure A.4: Boxplot of the meter loads at Zone 4

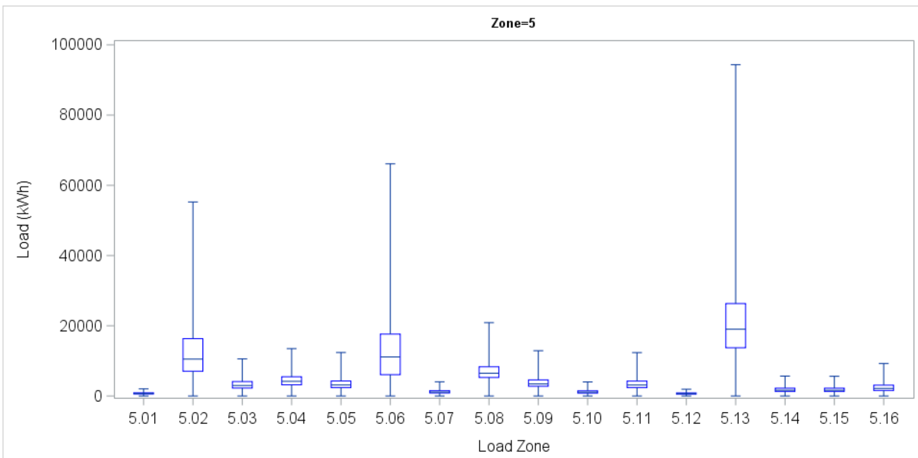

Figure A.5: Boxplot of the meter loads at Zone 5

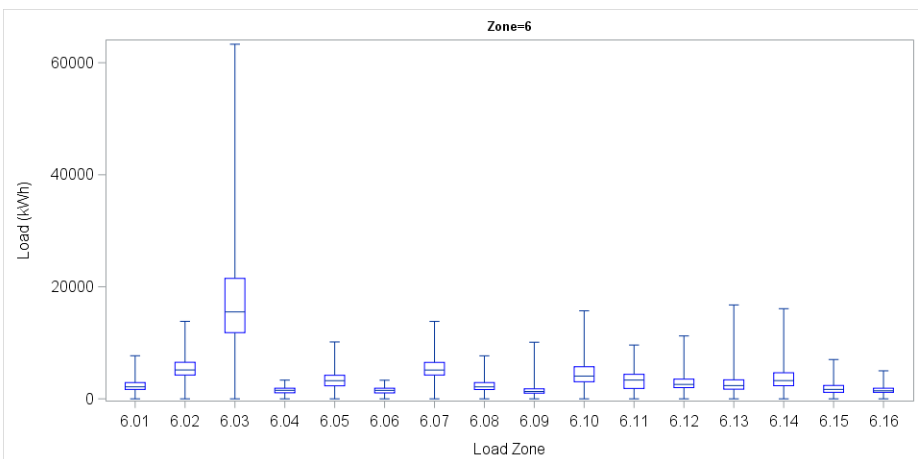

Figure A.6: Boxplot of the meter loads at Zone 6

2.

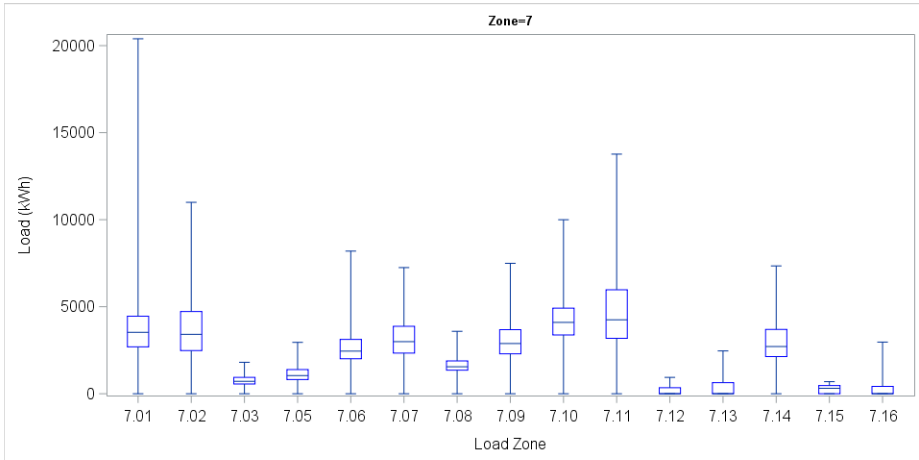

Figure A.7: Boxplot of the meter loads at Zone 7

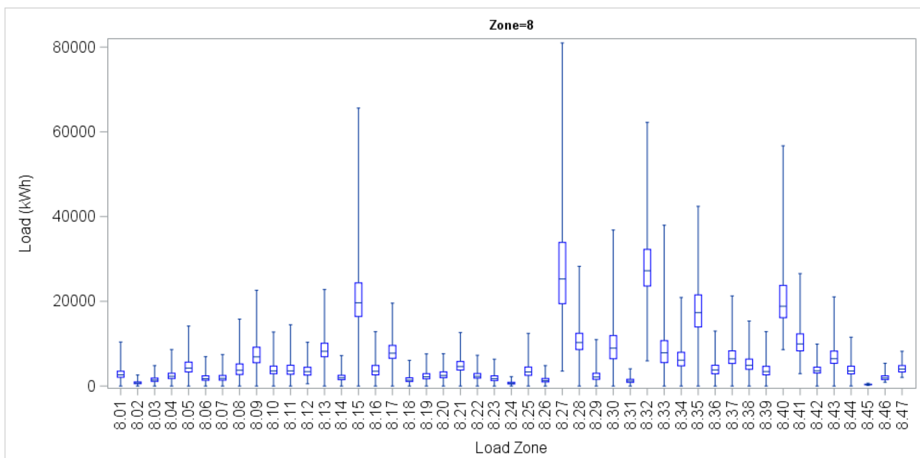

Figure A.8: Boxplot of the meter loads at Zone 8

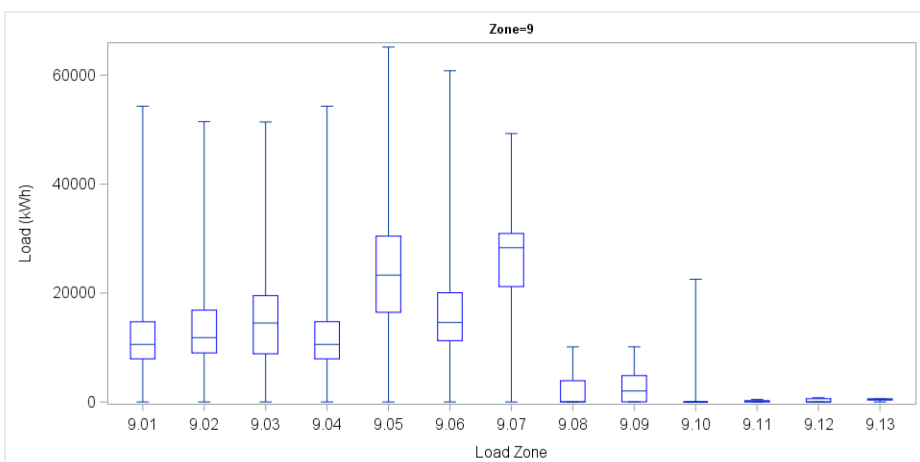

Figure A.9: Boxplot of the meter loads at Zone 9

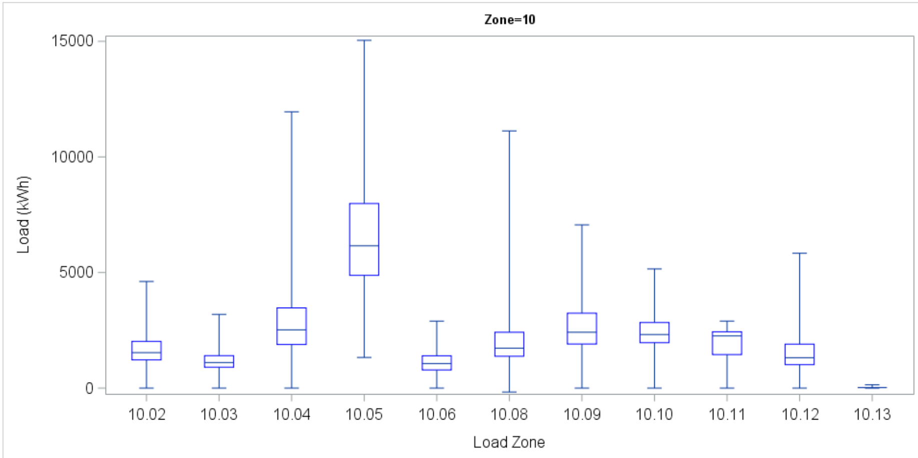

Figure A.10: Boxplot of the meter loads at Zone 10

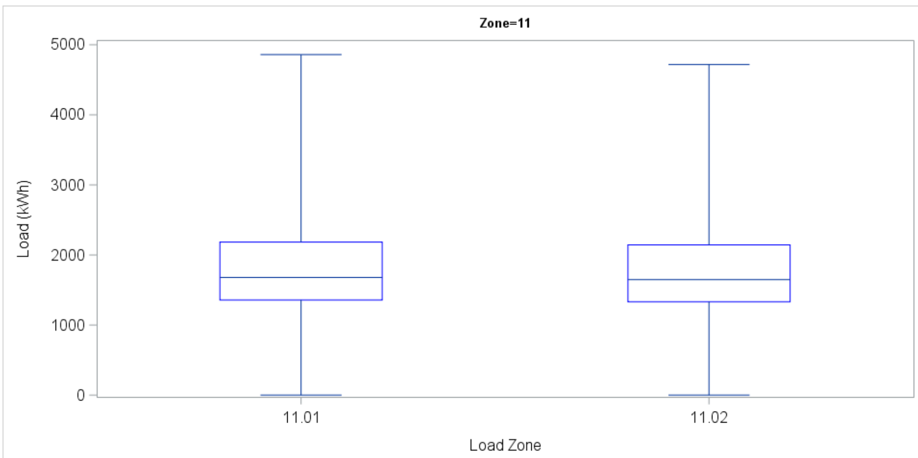

Figure A.11: Boxplot of the meter loads at Zone 11

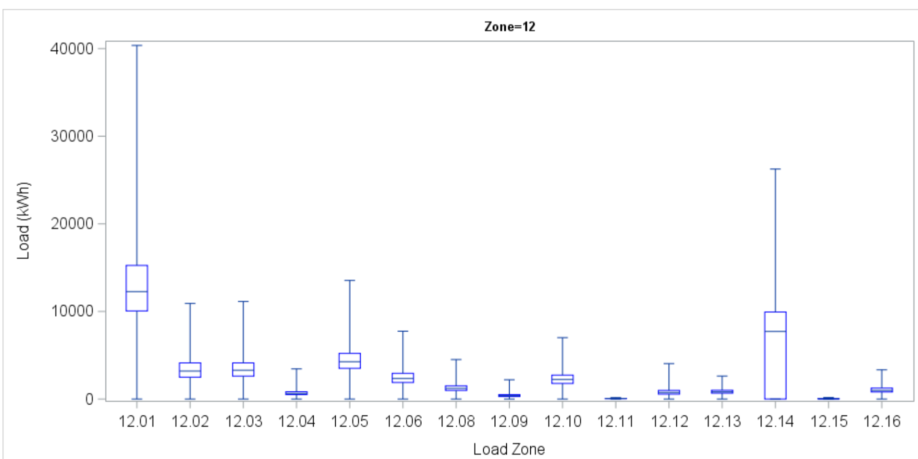

Figure A.12: Boxplot of the meter loads at Zone 12

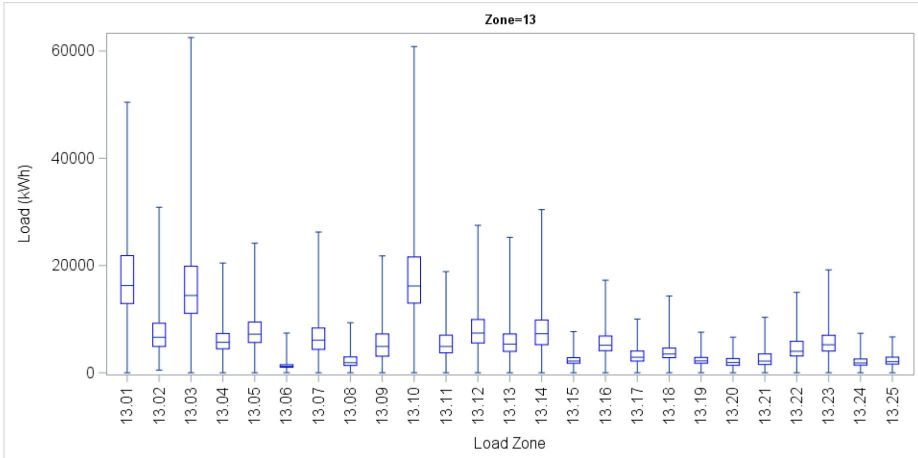

Figure A.13: Boxplot of the meter loads at Zone 13

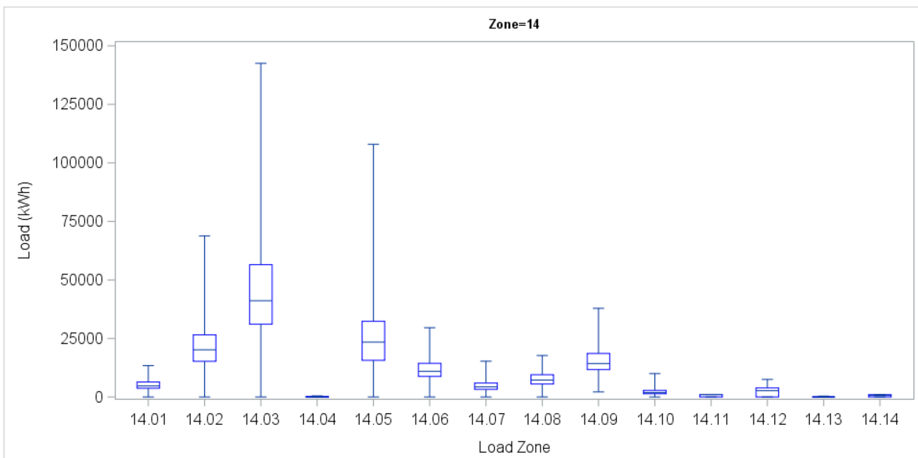

Figure A.14: Boxplot of the meter loads at Zone 14

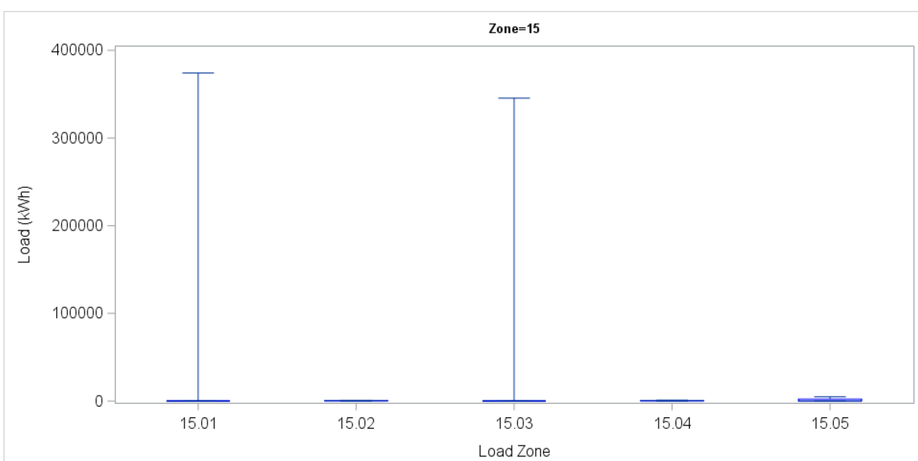

Figure A.15: Boxplot of the meter loads at Zone 15

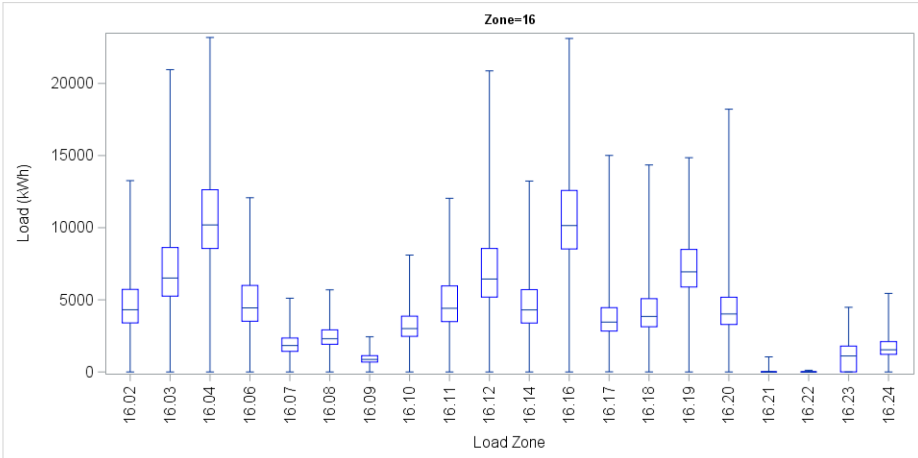

Figure A.16: Boxplot of the meter loads at Zone 16

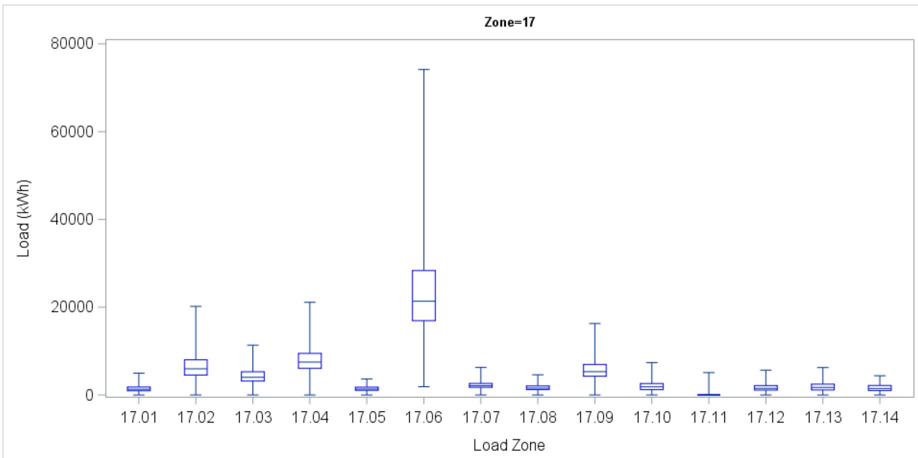

Figure A.17: Boxplot of the meter loads at Zone 17

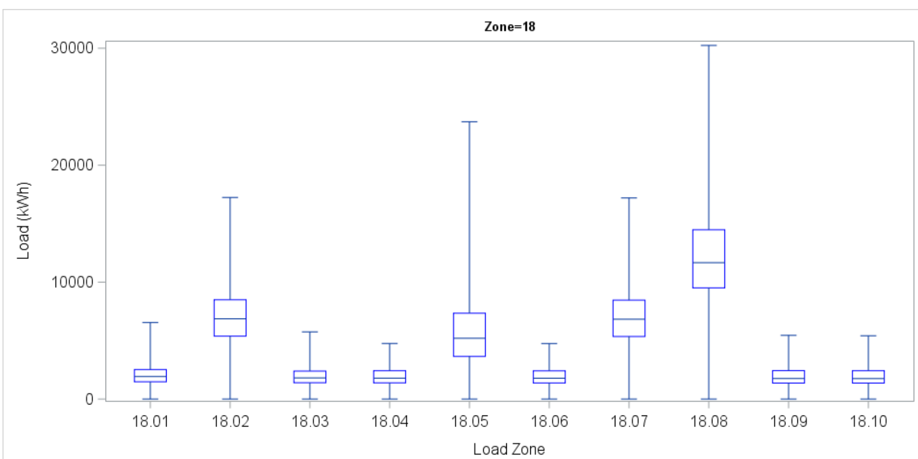

Figure A.18: Boxplot of the meter loads at Zone 18

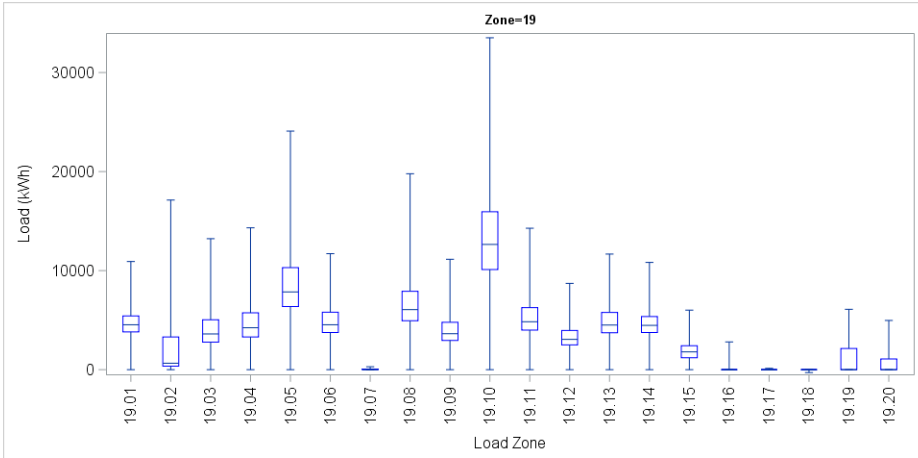

Figure A.19: Boxplot of the meter loads at Zone 19

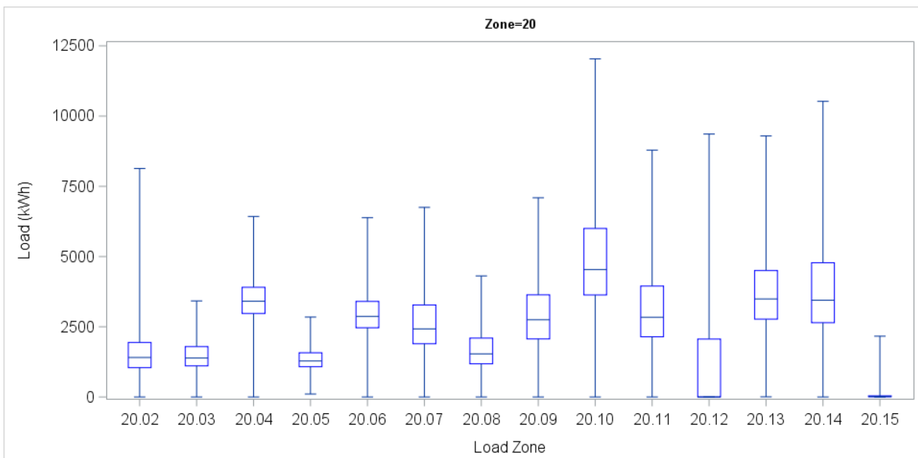

Figure A.20: Boxplot of the meter loads at Zone 20

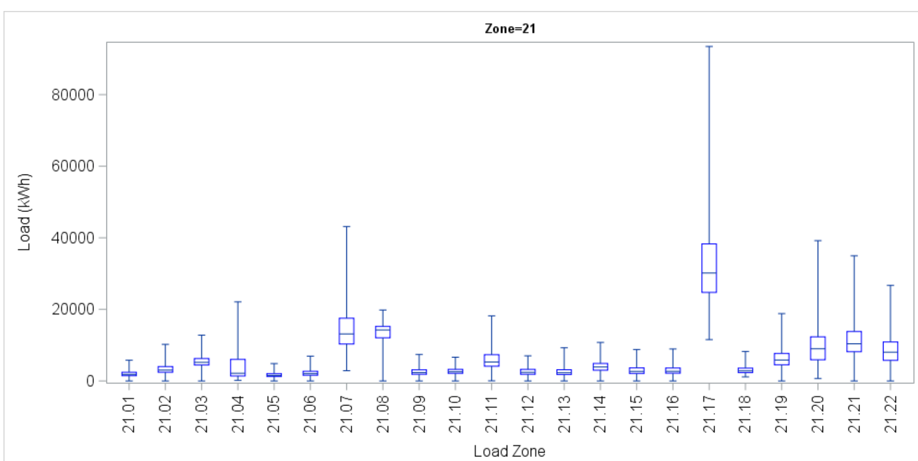

Figure A.21: Boxplot of the meter loads at Zone 21

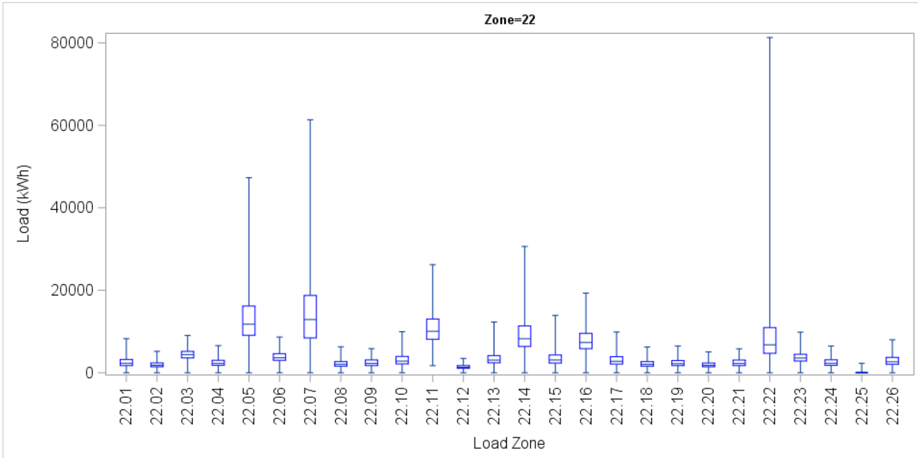

Figure A.22: Boxplot of the meter loads at Zone 22

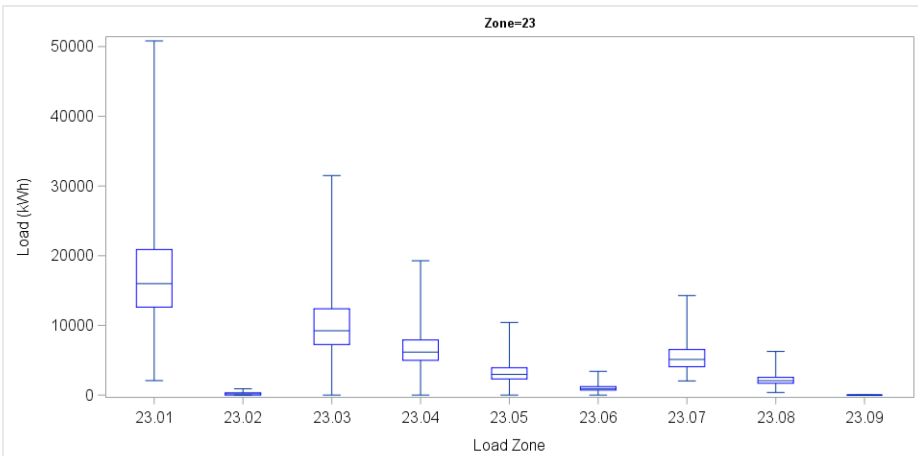

Figure A.23: Boxplot of the meter loads at Zone 23

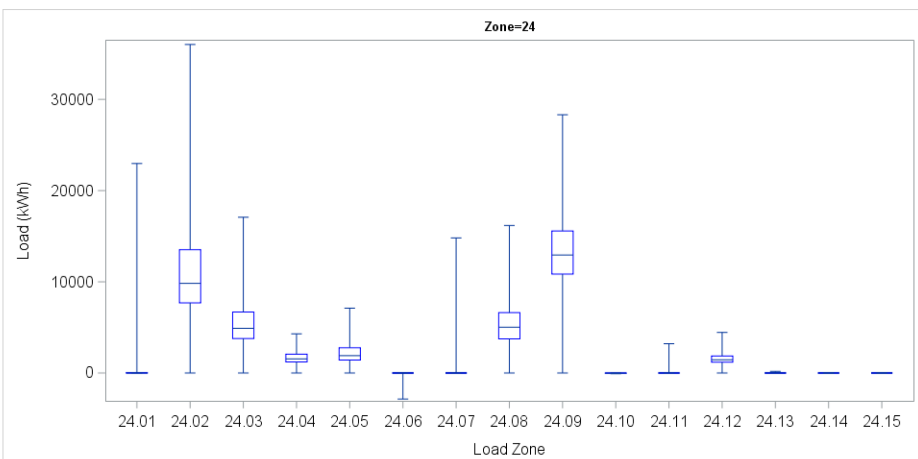

Figure A.24: Boxplot of the meter loads at Zone 24

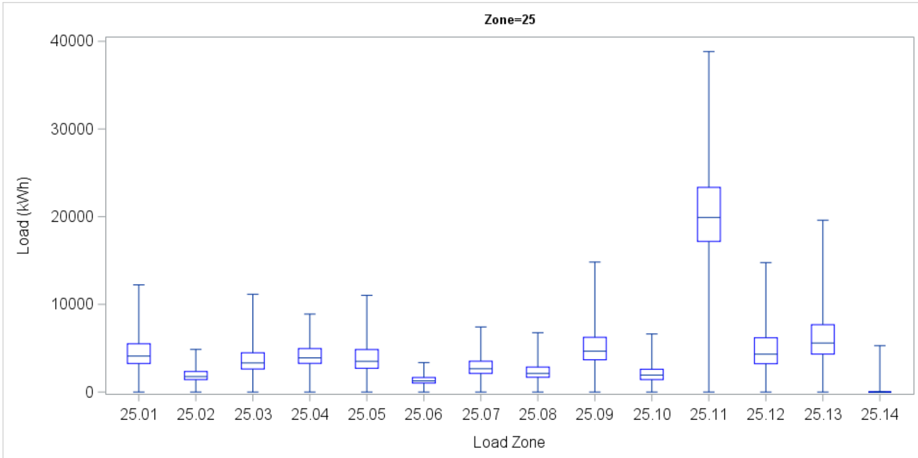

Figure A.25 Boxplot of the meter loads at Zone 25

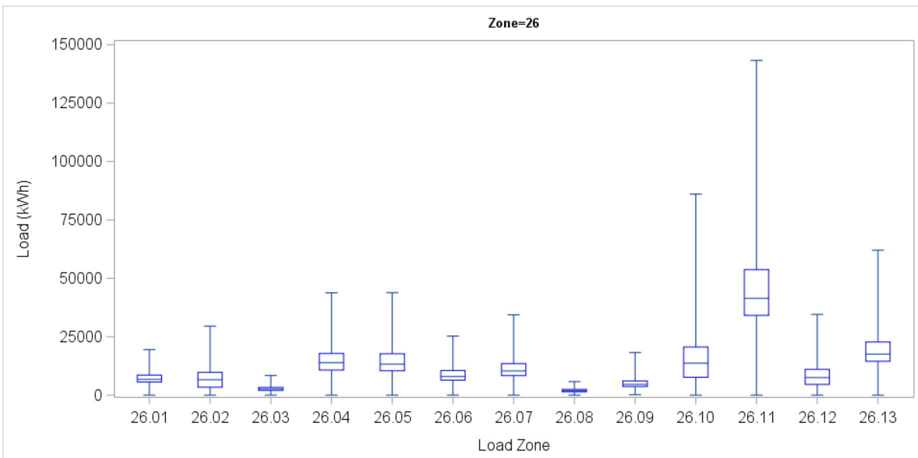

Figure A.26: Boxplot of the meter loads at Zone 26

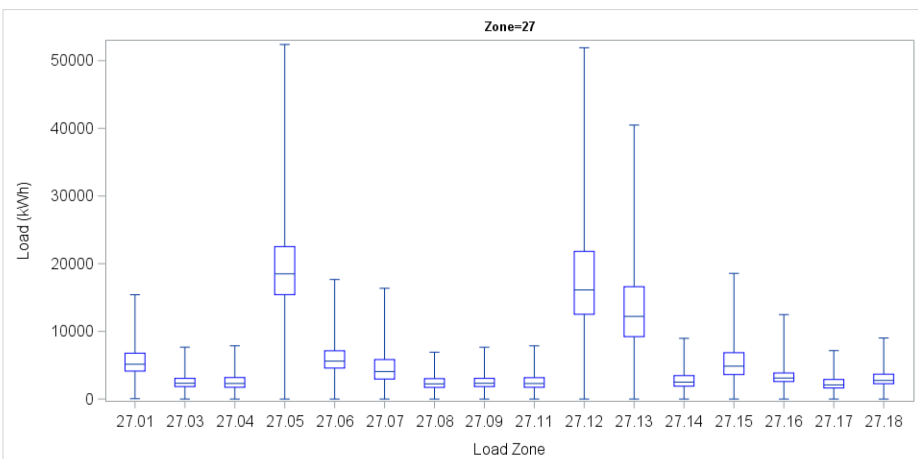

Figure A.27: Boxplot of the meter loads at Zone 27

Appendix B: Load Transfer Detection Results

ID	Load Zone	Year	$Meter_i$	$Meter_j$	MFM Rank	MFM Greedy	MBM Rank	MBM Greedy
1	1	2006	1.4	1.11	1	Yes	5	Yes
2	1	2008	1.2	1.12	1	Yes	10	Yes
3	2	2006	2.3	2.4	2	Yes	1	Yes
4	2	2007	2.3	2.4	1	Yes	1	Yes
5	2	2008	2.3	2.4	25	Yes	1	Yes
6	2	2009	2.3	2.4	28	Yes	1	Yes
7	2	2010	2.3	2.4	10	Yes	1	Yes
8	2	2011	2.3	2.4	13	Yes	1	Yes
9	2	2012	2.3	2.4	16	Yes	1	Yes
10	2	2013	2.3	2.4	1	Yes	1	Yes
11	2	2014	2.3	2.4	3	Yes	1	Yes
12	2	2015	2.3	2.4	8	Yes	1	Yes
13	2	2016	2.3	2.4	8	Yes	1	Yes
14	3	2007	3.2	3.8	4	No	5	No
15	3	2008	3.3	3.7	6	No	.	No
16	3	2009	3.8	3.2	4	No	.	Yes
17	3	2009	3.2	3.6	1	Yes	1	Yes
18	3	2010	3.8	3.2	1	Yes	4	No
19	3	2010	3.4	3.2	2	No	1	Yes
20	3	2011	3.8	3.2	4	Yes	3	No
21	3	2013	3.10	3.1	5	No	1	Yes
22	3	2013	3.8	3.2	8	No	5	No
23	3	2013	3.6	3.2	4	Yes	2	Yes
24	3	2014	3.4	3.2	9	No	2	Yes
25	3	2014	3.8	3.2	4	Yes	11	No
26	3	2015	3.6	3.2	3	Yes	4	No
27	3	2015	3.2	3.8	5	No	3	Yes
28	3	2015	3.1	3.10	1	Yes	5	Yes
29	3	2016	3.10	3.1	4	No	.	No
30	3	2016	3.6	3.2	14	No	2	No
31	5	2007	5.6	5.13	1	Yes	2	No
32	5	2008	5.6	5.13	1	Yes	1	Yes
33	5	2010	5.2	5.6	9	No	25	No
34	5	2010	5.6	5.13	1	Yes	2	Yes
35	5	2011	5.3	5.9	10	No	8	Yes

ID	Load Zone	Year	$Meter_i$	$Meter_j$	MFM Rank	MFM Greedy	MBM Rank	MBM Greedy
36	5	2011	5.2	5.13	5	No	17	No
37	5	2011	5.6	5.13	2	No	1	Yes
38	5	2012	5.2	5.13	1	Yes	1	Yes
39	5	2012	5.6	5.13	2	No	4	No
40	5	2013	5.2	5.13	2	No	.	No
41	5	2013	5.6	5.13	3	No	1	Yes
42	5	2014	5.2	5.6	2	Yes	.	No
43	5	2014	5.2	5.13	1	Yes	.	No
44	5	2014	5.6	5.13	3	No	1	Yes
45	5	2015	5.2	5.6	1	Yes	3	No
46	5	2016	5.2	5.6	3	No	15	No
47	5	2016	5.2	5.13	1	Yes	5	No
48	5	2016	5.6	5.13	2	No	3	No
49	6	2009	6.9	6.10	29	No	2	No
50	6	2011	6.13	6.14	25	No	8	No
51	6	2012	6.9	6.10	81	No	.	No
52	6	2012	6.11	6.12	11	Yes	.	No
53	6	2012	6.5	6.15	1	Yes	11	No
54	6	2012	6.15	6.16	5	No	1	Yes
55	6	2013	6.11	6.12	1	Yes	.	No
56	6	2014	6.9	6.10	29	No	.	No
57	8	2006	8.43	8.34	2	Yes	2	Yes
58	8	2006	8.17	8.37	1	Yes	1	Yes
59	8	2007	8.15	8.32	38	No	2	Yes
60	8	2007	8.17	8.37	1	Yes	1	Yes
61	8	2008	8.36	8.34	1	Yes	8	No
62	8	2014	8.32	8.15	48	No	10	Yes
63	8	2015	8.32	8.15	151	No	18	No
64	9	2006	9.1	9.5	4	No	7	No
65	9	2006	9.3	9.5	5	No	6	No
66	9	2007	9.2	9.7	1	Yes	1	Yes
67	9	2008	9.3	9.5	14	No	1	Yes
68	9	2008	9.1	9.6	31	No	7	Yes
69	9	2008	9.4	9.6	30	No	8	No
70	9	2009	9.3	9.5	2	Yes	2	Yes

ID	Load Zone	Year	$Meter_i$	$Meter_j$	MFM Rank	MFM Greedy	MBM Rank	MBM Greedy
71	9	2009	9.2	9.6	14	No	3	Yes
72	9	2009	9.8	9.9	1	Yes	1	Yes
73	9	2010	9.3	9.5	1	Yes	15	No
74	9	2010	9.4	9.6	4	No	4	No
75	9	2010	9.1	9.6	3	Yes	2	Yes
76	9	2010	9.8	9.9	2	Yes	1	Yes
77	9	2011	9.3	9.5	32	No	7	No
78	9	2011	9.1	9.6	7	No	.	No
79	9	2011	9.4	9.6	6	No	.	No
80	9	2011	9.8	9.9	11	No	1	Yes
81	9	2012	9.3	9.5	1	Yes	10	No
82	9	2012	9.1	9.5	3	No	15	No
83	9	2012	9.4	9.5	2	No	16	No
84	9	2012	9.1	9.6	10	No	12	No
85	9	2012	9.4	9.6	9	No	13	No
86	9	2012	9.8	9.9	4	Yes	1	Yes
87	9	2013	9.1	9.6	25	No	4	No
88	9	2013	9.4	9.6	24	No	5	No
89	9	2013	9.8	9.9	1	Yes	1	Yes
90	9	2014	9.3	9.5	9	Yes	3	Yes
91	9	2014	9.8	9.9	7	No	1	Yes
92	9	2015	9.3	9.5	7	Yes	4	No
93	9	2015	9.2	9.6	39	No	7	No
94	9	2015	9.1	9.6	51	No	27	No
95	9	2015	9.4	9.6	52	No	26	No
96	9	2015	9.8	9.9	6	Yes	1	Yes
97	9	2016	9.1	9.5	18	No	.	No
98	9	2016	9.4	9.6	5	Yes	9	No
99	9	2016	9.2	9.6	13	No	3	No
100	9	2016	9.1	9.6	6	No	10	No
101	9	2016	9.8	9.9	1	Yes	1	Yes
102	10	2009	10.4	10.12	8	Yes	1	Yes
103	10	2012	10.8	10.12	25	No	2	No
104	12	2006	12.1	12.14	1	Yes	1	Yes
105	12	2009	12.9	12.10	1	Yes	.	No

ID	Load Zone	Year	$Meter_i$	$Meter_j$	MFM Rank	MFM Greedy	MBM Rank	MBM Greedy
106	12	2010	12.9	12.10	1	Yes	.	No
107	12	2012	12.5	12.6	2	Yes	2	No
108	13	2009	13.7	13.16	3	Yes	1	Yes
109	13	2009	13.1	13.17	17	No	2	Yes
110	13	2009	13.5	13.18	5	No	3	Yes
111	13	2010	13.4	13.18	1	Yes	.	No
112	13	2011	13.4	13.18	2	Yes	.	No
113	13	2011	13.9	13.19	14	No	.	No
114	13	2014	13.8	13.21	1	Yes	.	No
115	13	2014	13.9	13.22	3	No	.	No
116	13	2014	13.12	13.23	6	No	1	Yes
117	14	2007	14.3	14.5	2	No	1	Yes
118	14	2008	14.3	14.2	1	Yes	1	Yes
119	14	2008	14.3	14.5	2	No	9	No
120	14	2012	14.1	14.12	1	Yes	1	Yes
121	14	2013	14.3	14.5	4	No	1	Yes
122	14	2014	14.2	14.3	43	No	.	No
123	14	2014	14.3	14.5	21	No	2	Yes
124	16	2009	16.4	16.19	1	Yes	2	No
125	16	2009	16.4	16.20	2	No	1	Yes
126	16	2011	16.17	16.18	29	No	1	Yes
127	16	2011	16.19	16.20	1	Yes	4	Yes
128	16	2014	16.17	16.18	1	Yes	1	Yes
129	16	2014	16.19	16.20	2	Yes	4	No
130	17	2006	17.10	17.11	1	Yes	1	Yes
131	17	2015	17.10	17.13	1	Yes	1	Yes
132	17	2016	17.10	17.13	6	No	1	Yes
133	17	2016	17.12	17.14	1	Yes	.	No
134	18	2007	18.3	18.5	18	No	1	Yes
135	18	2008	18.5	18.8	3	No	.	No
136	18	2008	18.2	18.8	1	Yes	.	No
137	18	2010	18.5	18.8	1	Yes	1	Yes
138	18	2011	18.5	18.8	1	Yes	1	Yes
139	18	2012	18.5	18.8	1	Yes	1	Yes
140	18	2013	18.4	18.9	1	Yes	3	No

ID	Load Zone	Year	$Meter_i$	$Meter_j$	MFM Rank	MFM Greedy	MBM Rank	MBM Greedy
141	18	2013	18.6	18.10	4	Yes	.	No
142	18	2016	18.5	18.8	1	Yes	1	Yes
143	19	2007	19.9	19.11	3	Yes	1	Yes
144	19	2013	19.2	19.3	1	Yes	.	No
145	20	2008	20.12	20.14	1	Yes	1	Yes
146	20	2015	20.2	20.9	1	Yes	1	Yes
147	22	2007	22.7	22.22	3	Yes	1	Yes
148	22	2009	22.7	22.22	21	Yes	3	Yes
149	22	2009	22.3	22.23	1	Yes	1	Yes
150	22	2010	22.7	22.22	1	Yes	3	Yes
151	22	2011	22.7	22.22	3	Yes	.	No
152	22	2011	22.9	22.24	1	Yes	2	No
153	22	2012	22.7	22.22	1	Yes	4	Yes
154	22	2014	22.1	22.10	21	No	8	No
155	22	2014	22.7	22.22	1	Yes	4	Yes
156	22	2015	22.8	22.12	48	No	15	No
157	22	2015	22.7	22.22	1	Yes	1	Yes
158	22	2016	22.13	22.15	2	Yes	8	No
159	22	2016	22.7	22.22	1	Yes	3	No
160	23	2009	23.1	23.3	1	Yes	1	Yes
161	24	2011	24.7	24.8	1	Yes	.	No
162	24	2011	24.5	24.11	9	No	1	Yes
163	24	2012	24.7	24.8	1	Yes	2	No
164	24	2013	24.7	24.8	9	No	2	Yes
165	24	2014	24.7	24.8	1	Yes	1	Yes
166	24	2015	24.1	24.2	1	Yes	1	Yes
167	26	2009	26.10	26.11	16	No	2	Yes
168	26	2009	26.4	26.12	3	Yes	4	No
169	26	2009	26.2	26.12	5	No	1	Yes
170	26	2010	26.10	26.13	1	Yes	1	Yes
171	26	2011	26.10	26.13	4	No	4	Yes
172	26	2013	26.2	26.12	1	Yes	1	Yes
173	26	2015	26.10	26.13	1	Yes	1	Yes
174	26	2016	26.10	26.11	3	No	2	No
175	26	2016	26.10	26.13	1	Yes	1	Yes
176	27	2012	27.7	27.15	1	Yes	.	No
177	27	2015	27.8	27.17	1	Yes	10	No

Appendix C: Load Forecasting Results

Table C.1: Results for the single meters

Meter	Raw	Clean Load	Clean Load + Weather
1.1	9.77	9.68	9.67
1.2	10.04	10.00	10.00
1.3	8.82	8.68	8.67
1.7	16.11	16.01	16.03
1.8	9.46	9.39	9.36
1.9	19.54	19.06	19.07
1.12	20.18	20.37	20.33
2.1	7.03	6.94	6.94
2.2	5.53	5.50	5.51
2.5	5.70	5.65	5.64
3.9	8.95	8.90	8.86
4.1	17.83	18.01	17.95
5.3	9.24	9.07	8.99
5.4	15.51	15.09	15.06
5.5	9.20	9.04	9.06
5.7	21.38	21.08	21.08
5.9	10.84	10.80	10.78
5.10	8.44	8.29	8.30
5.11	9.24	9.07	9.10
5.12	23.90	23.31	23.28
5.14	10.14	9.86	9.90
5.15	8.37	8.22	8.21
6.1	9.67	9.61	9.60
6.2	8.97	9.04	9.04
6.3	15.05	15.13	15.09
6.4	11.38	11.58	11.54
6.6	11.44	11.63	11.59
6.7	7.77	7.91	7.94
6.8	9.75	9.69	9.68
6.13	17.45	17.23	17.10
6.14	14.99	14.37	14.25
6.15	19.47	18.35	18.46
6.16	7.87	7.71	7.78
7.1	10.31	10.28	10.28
7.2	10.96	10.79	10.72

Table C.1.cont.

Meter	Raw	Clean Load	Clean Load + Weather
7.5	9.34	9.27	9.26
7.6	9.50	7.10	7.11
7.8	10.15	10.13	10.11
7.9	8.90	8.89	8.89
7.10	15.40	15.30	15.32
7.11	17.63	17.42	17.47
7.14	24.21	21.70	21.71
8.1	8.87	8.57	8.54
8.2	17.67	17.40	17.38
8.3	9.58	9.40	9.38
8.4	17.52	16.93	16.95
8.5	7.88	7.79	7.74
8.6	7.51	7.37	7.36
8.7	9.18	9.13	9.05
8.8	8.31	8.28	8.21
8.9	6.73	6.73	6.68
8.10	7.12	7.09	7.10
8.11	7.75	7.64	7.58
8.12	8.27	8.25	8.23
8.13	5.67	5.62	5.61
8.14	8.17	8.13	8.12
8.16	7.83	7.79	7.72
8.17	6.18	6.08	6.03
8.18	8.01	7.98	7.96
8.19	7.87	7.85	7.87
8.21	9.39	10.02	10.06
8.22	6.17	6.17	6.15
8.23	10.38	10.34	10.34
8.24	9.27	8.46	8.56
8.25	7.65	7.52	7.52
8.26	7.46	7.42	7.40
8.27	7.14	7.08	7.04
8.28	5.56	5.68	5.65
8.29	8.41	8.31	8.30
8.30	6.85	6.79	6.76

Table C.1.cont.

Meter	Raw	Clean Load	Clean Load + Weather
8.31	8.96	8.65	8.62
8.33	8.81	8.67	8.63
8.34	13.87	13.69	13.65
8.35	7.22	7.17	7.14
8.36	7.99	8.00	7.99
8.37	6.32	6.15	6.12
8.38	19.40	19.25	19.16
8.39	21.52	21.25	21.17
8.40	5.61	5.53	5.51
8.41	6.39	6.37	6.34
8.42	5.32	5.28	5.27
8.43	6.73	6.63	6.59
8.44	8.95	8.93	8.90
8.45	13.92	13.85	13.88
9.7	14.70	14.80	14.76
10.2	10.35	10.39	10.41
10.3	8.35	8.36	8.43
10.4	13.34	11.20	11.05
10.5	7.98	7.87	7.88
10.6	11.43	11.42	11.41
10.8	11.37	11.32	11.31
10.9	7.87	7.75	7.76
10.10	7.03	6.97	6.99
10.12	18.57	16.08	15.87
12.1	8.36	8.09	8.09
12.2	6.95	6.90	6.92
12.3	14.50	14.05	14.06
12.4	8.77	8.63	8.64
12.5	7.24	7.20	7.20
12.6	7.05	7.01	7.01
12.8	10.39	10.16	10.17
12.9	8.73	9.08	9.11
12.10	7.13	7.04	7.04
12.11	18.57	18.90	18.91
12.12	28.41	28.29	28.31

Table C.1.cont.

Meter	Raw	Clean Load	Clean Load + Weather
12.13	8.35	8.34	8.36
12.15	14.98	14.21	14.24
12.16	18.52	19.55	19.59
13.1	7.71	7.67	7.65
13.3	9.78	9.54	9.53
13.4	7.90	7.53	7.49
13.5	6.29	6.25	6.21
13.6	7.29	7.35	7.36
13.7	9.18	9.16	9.07
13.10	6.55	6.56	6.52
13.11	9.04	8.96	8.85
13.13	14.43	13.53	13.55
13.14	7.25	7.20	7.11
13.15	6.78	6.78	6.73
13.16	8.36	8.30	8.26
13.17	8.90	8.80	8.71
13.18	5.82	5.79	5.73
13.19	15.10	14.86	14.92
13.20	9.65	9.60	9.54
14.1	6.72	6.69	6.64
14.6	21.25	21.24	21.14
14.7	20.61	20.62	20.60
14.8	10.18	10.04	10.00
14.9	7.80	7.78	7.72
16.2	20.40	20.41	20.42
16.3	62.75	60.70	60.75
16.6	8.11	8.12	8.05
16.7	10.90	10.58	10.55
16.8	7.71	7.67	7.65
16.10	7.98	7.95	7.88
16.11	8.17	8.18	8.11
16.14	20.42	20.43	20.44
17.1	13.05	13.01	13.05
17.2	9.26	9.27	9.26
17.3	15.22	14.82	14.83

Table C.1.cont.

Meter	Raw	Clean Load	Clean Load + Weather
17.4	9.96	9.94	9.94
17.6	6.95	6.84	6.83
17.7	7.64	7.56	7.54
17.8	7.79	7.73	7.73
17.9	10.83	10.41	10.37
18.8	7.49	7.45	7.42
18.9	10.47	10.44	10.44
18.10	13.67	13.64	13.65
19.1	18.61	18.52	18.51
19.2	7.95	7.82	7.74
19.4	8.16	8.28	8.28
19.8	7.21	7.16	7.17
19.10	7.03	6.88	6.86
19.11	8.89	8.87	8.85
19.12	7.60	7.56	7.55
19.14	5.85	5.76	5.74
19.15	20.41	19.63	19.65
20.3	9.94	9.90	9.88
20.4	6.62	6.64	6.63
20.5	7.52	7.49	7.48
20.6	28.07	27.94	27.98
20.7	7.92	7.93	7.94
20.8	8.16	8.13	8.14
20.10	7.81	7.77	7.78
20.11	10.00	10.06	10.02
20.13	11.20	10.79	10.71
20.14	9.53	9.48	9.46
21.1	7.32	7.27	7.22
21.2	7.14	7.07	7.07
21.3	5.80	5.75	5.72
21.4	12.42	12.32	12.37
21.5	7.38	7.43	7.35
21.6	7.46	7.37	7.37
21.7	7.69	7.64	7.62
21.8	10.95	12.01	12.03

Table C.1.cont.

Meter	Raw	Clean Load	Clean Load + Weather
21.9	9.13	8.98	8.96
21.10	7.55	7.59	7.55
21.11	7.32	7.30	7.21
21.12	7.80	7.73	7.64
21.13	15.17	15.20	15.24
21.14	6.14	6.09	6.05
21.15	7.71	7.67	7.61
21.16	7.06	7.00	6.95
21.17	6.03	6.03	6.01
21.18	6.47	6.42	6.41
21.19	8.79	8.79	8.75
21.20	6.94	6.89	6.88
21.21	6.50	6.44	6.43
21.22	28.12	27.80	27.88
22.2	19.39	19.45	19.43
22.4	14.59	14.57	14.54
22.5	8.10	7.98	7.90
22.6	7.50	7.36	7.32
22.11	8.85	8.80	8.75
22.14	10.58	9.72	9.61
22.16	8.58	8.59	8.54
22.20	10.09	10.09	10.06
12.15	14.98	14.21	14.24
22.24	9.43	9.37	9.34
23.1	6.40	6.36	6.36
23.3	6.97	6.93	6.92
23.4	21.49	21.26	21.26
23.5	7.45	7.42	7.41
23.6	7.98	7.90	7.90
23.7	8.42	8.03	8.06
23.8	7.90	7.89	7.89
24.3	8.76	8.69	8.67
24.4	9.14	9.10	9.05
24.5	22.88	22.70	22.76
24.9	7.86	7.84	7.88

Table C.1.cont.

Meter	Raw	Clean Load	Clean Load + Weather
24.12	16.17	15.76	15.71
25.1	7.99	7.92	7.89
25.2	17.29	17.22	17.16
25.3	11.37	11.33	11.29
25.4	61.90	61.74	61.76
25.5	16.92	16.95	16.88
25.6	12.12	12.03	11.99
25.9	13.42	13.41	13.37
25.10	10.82	10.70	10.68
25.11	9.39	9.36	9.36
25.12	14.98	14.94	14.87
25.13	7.67	7.60	7.53
26.3	8.40	8.35	8.31
26.5	7.83	7.65	7.60
26.6	7.80	7.76	7.70
26.7	10.18	10.05	9.99
26.8	12.39	12.04	12.01
26.9	7.26	7.11	7.09
27.4	9.43	9.45	9.46
27.5	7.36	7.20	7.18
27.6	6.71	6.59	6.57
27.11	9.48	9.49	9.51
27.12	8.31	8.10	8.03
27.13	23.42	23.47	23.46
27.14	8.95	8.85	8.80

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