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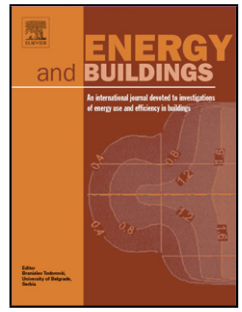

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Authors: Charalampos Marmaras, Amir Javed, Liana Cipcigan, Omer Rana

PII: S0378-7788(17)30592-3
DOI: http://dx.doi.org/doi:10.1016/j.enbuild.2017.02.046
Reference: ENB 7407

To appear in: *ENB*

Received date: 11-3-2016
Revised date: 9-1-2017
Accepted date: 19-2-2017

Please cite this article as: Charalampos Marmaras, Amir Javed, Liana Cipcigan, Omer Rana, Predicting the energy demand of buildings during triad peaks in GB, Energy and Buildings http://dx.doi.org/10.1016/j.enbuild.2017.02.046

Predicting the energy demand of buildings during triad peaks in GB

Charalampos Marmaras*, Amir Javed, Dr. Liana Cipcigan and Prof. Omer Rana
*marmarasc@cardiff.ac.uk

Cardiff University

Highlights

Ms. Ref. No.: ENB-D-16-00506 – Energy and Buildings
Title: Predicting the energy demand of buildings during triad peaks in GB

- A stochastic model was developed to calculate the probability of having a "triad" peak on a daily and half-hourly basis.
- Real weather data were analysed and included in the model to increase its forecasting accuracy.
- An artificial neural network forecasting model was developed to predict the power demand of the building at the periods when a "triad" peak is more likely to occur.
- The model was trained and tested on real "triad" peak data and building electricity demand data from Manchester.

Abstract - A model-based approach is described to forecast triad periods for commercial buildings, using a multi-staged analysis that takes a number of different data sources into account, with each stage adding more accuracy to the model. In the first stage, a stochastic model is developed to calculate the probability of having a "triad" on a daily and half-hourly basis and to generate an alert to the building manager if a triad is detected. In the second stage, weather data is analysed and included in the model to increase its forecasting accuracy. In the third stage, an ANN forecasting model is developed to predict the power demand of the building at the periods when a "triad" peak is more likely to occur. The stochastic model has been trained on "triad" peak data from 1990 onwards, and validated against the actual UK "triad" dates and times over the period 2014/2015. The ANN forecasting model was trained on electricity demand data from six commercial buildings at a business park for one year. Local weather data for the same period were analysed and included to improve model accuracy. The electricity demand of each building on an actual "triad" peak date and time was predicted successfully, and an overall forecasting accuracy of 97.6% was demonstrated for the buildings being considered in the study. This measurement based study can be generalised and the proposed methodology can be translated to other similar built environments.

Keywords – triad period, energy demand, neural network, weather sensitivity analysis

1 Introduction

The "triad season" is the four-month period from 1st of November to the end of February, during which National Grid looks back to find the three half-hour periods when the electricity demand was highest in GB [1]. These three periods, also known as "triad" periods, must be separated by at least ten days and are used by National Grid to estimate the average peak demand of each distribution network operator (DNO) for that winter. According to its corresponding peak demand, each DNO pays a "capacity charge" to National Grid to ensure the availability of this peak amount of electricity [2]. These capacity costs are shifted from the DNOs to the electricity suppliers, and the electricity suppliers transfer this cost to their customers (end-users) by charging extra for the electricity used during a "triad" period.

The domestic low-consumption customers have this extra charge built into an all-inclusive electricity rate so they do not notice any difference in their electricity charges on a "triad" period. On the other hand, the high-consumption customers (usually commercial/industrial) may be charged a higher rate of £/MWh for the electricity they use during the "triad" periods. Depending on their agreement with the utility company, they might even be separately invoiced for these charges. These charges are currently (approximately) £45/kW, meaning that a high-consumption consumer with an average consumption of 2MW would have to pay £90,000 every year for their contribution to the system's peak demand. The "triad" periods of each year are announced by National Grid after the end of the "triad season", usually sometime in March. Recent studies indicate that the "triad" charges are going to increase in the following years, and could reach £72/kW by 2020 [3]. Consequently, there is a great deal of interest from the high-consumption customers to know beforehand the "triad" periods so they can reduce their electricity consumption and their bills [4]. A typical case is that of Saint-Gobain which, in order to tackle the “triad” cost, switched off industrial machinery and rescheduled factory operation for a short period of time from around 4pm-6pm, the period which is most likely to witness a “triad” peak. By doing this the company was able to save around 11% of energy costs (equating to a financial value of £165,000) [5].

Many suppliers offer warning services to their customers in order to help them reduce their “triad” charges (e.g. NPower [6]). Predicting the “triad” peaks meets a number of challenges, one of them being the so-called “negative feedback” problem according to which knowing about a “triad” peak could in fact prevent it [7]. The “triad” peaks are mainly caused by small commercial buildings and domestic houses, rather than the large commercial/industrial consumers. Consequently “triad” peaks are largely dependent on weather, and they usually coincide with cold snaps [8]. Unfortunately that means that “triad” peaks are more unpredictable in mild winters. Considering the complexity associated with predicting triads, probabilistic and fuzzy approaches can be utilised for estimating the “triad” peaks. There is a need for a tool that decodes these “fuzzy” correlations in a simple yet effective manner, and could be directly utilised by a (non-expert) building manager.

However, having information about future “triad” peaks is not enough for the building managers to reduce their bills. Information about the electricity demand of their buildings on a “triad” period is also necessary, in order to identify the buildings that contribute the most to these extra charges. Knowing future demand, building managers can identify those buildings which operate with unnecessary loads and attempt to reduce their electricity consumption. The weather has a significant impact on the electricity demand of a building, as heating during this period could lead to increase in their energy consumption. In order to predict the energy consumption of a building, it is necessary to take local weather into account.

In this paper a predictive model is proposed that aims to assist the commercial building manager to reduce energy bills by predicting the “triad” peak dates and the building’s energy demand on those dates. The model consists of three stages/parts. In the first part, a stochastic model was developed to predict the triad days and hours for the next year. In the second part a sensitivity analysis was performed in order to calculate the impact of weather on the electricity demand of a commercial building. In the last part, a forecasting model was developed using Artificial Neural Networks (ANN) to forecast the building's energy demand at the most probable half hour a “triad” could occur. The model was evaluated using real weather and building energy consumption data from commercial buildings at a science park.

2 Related Work

Forecasting the peak electricity demand has been studied extensively. The studied approaches for forecasting models include semi-parametric regression [9], [10], time series modelling [11], exponential smoothing [12], Bayesian statistics [13], [14], time-varying splines [15], neural networks [16], [17], decomposition techniques [18]–[20], transfer functions [21], grey dynamic models [22], and judgmental forecasting [23]. These forecasts are usually characterized by their time horizon: i) short-term forecasts (five minutes to one week ahead) for ensuring system stability, ii) medium-term forecasts (one week to six months ahead) for maintenance scheduling, and iii) long-term forecasts (six months to ten years ahead) for network planning. While a point forecast provides an estimate of expected value of the future demand, probabilistic forecasts contain additional valuable information. Having access to prediction intervals, such as a lower and upper boundary of the forecast distribution [22] or a prediction density [24], would inform the decision maker of the uncertainty inherent in the forecast. Quantification of this forecast uncertainty is essential for managing the risk associated with decision making. Probabilistic methods which are able to capture the various factors that govern the electricity demand and forecast its peak can be found in [25]–[27].

Despite the extensive research work available on forecasting (single) peak demand of a power system, predicting the “triad” peaks has attracted very little attention globally. One obvious reason is that the “triad” charging system is found only in UK, as other countries use other ways to calculate their transmission network charges. Another reason is that many UK electricity suppliers are already providing warning services to their customers when a “triad” peak is expected to occur. These warnings however are often one day before the actual “triad” peak, not leaving enough time for customers to adjust their electricity requirements. To overcome this problem, the customers need to use their own probabilistic models in order to forecast the “triad” peaks in the beginning of the “triad” season. However, these models are often very complex and require a large amount of data for their calculations. A non-expert customer, like a building manager, is very unlikely to be able to operate these models or even have access to the required data for their calculations. There is a clear need for a “triad” prediction tool that is simple enough to be operated by the non-expert building manager, but which also provides satisfactory forecasts on the times of the future “triad” peaks.

However, knowledge about the future “triad” peaks is useless for the building managers unless the electricity demand of their buildings is also known in advance. Forecasting the electricity demand of a building is a well-studied subject. The prediction models need to consider many factors in order to accurately predict the daily, hourly or half-hourly power consumption of a building. These factors may be internal, like the geometrical characteristics of the building, the type and number of occupants, or they could be external factors like the weather. The existing approaches can be broadly classified as engineering, statistical and artificial intelligence based approaches.

The engineering models use details of physical characteristics, operational profiles and cost to calculate precisely the energy for each component of the building and simulate its operation [28]. The procedure for calculating the energy consumption of a building is also standardised by major organizations such as the International Organization for Standardization (ISO) and the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). Various tools such as DesignBuilder, EnergyPlus, TREAT etc. have been developed commercially to calculate the energy efficiency and the sustainability of a building. A list of such tools can be found in [29], hosted by the US

Department of Energy. However, these tools require detailed information about the building and its environment as an input and cannot be used by the non-expert building manager.

Another way to predict the energy consumption of a building is to use statistical regression models that correlate the power consumption with a number of influencing variables. These models are strongly dependent on the availability of historical data, and need a large dataset to produce accurate results. By using such a regression model, Lei and Hu [30] showed that a single variable linear model is able to predict the energy consumption in hot and cold weather conditions. Another regression model was developed in [31] to predict the annual energy consumption by using one day, one week and three month measurements. The results displayed strong influence on the forecast horizon as the errors were found to be up to 100% for one day, 30% for one week and 6% for three months data. An auto-regressive integrated moving average model was developed in [32] to forecast load profiles for the next day based on historical data records. This model was later enhanced with external inputs in order to predict the peak electricity demand for a building [33], [34].

Artificial intelligence methods have been found to be effective for solving complex non-linear problems. A comprehensive review of the application of computational intelligence techniques on building environments can be found in [35]. ANN has often been applied by researchers to predict the building's energy consumption in different environments. An ANN which predicted the long term energy demand, using short term energy data (2-5 weeks), was presented in [36]. Another interesting technique was used in [37], where the short term electricity demand was predicted by using two phases of an ANN. In phase one the weather variable was predicted using an ANN, and this output was then fed into a second ANN which predicted electricity consumption. In addition to ANN, support vector machines (SVM) are gaining popularity in predicting electricity consumption. Using SVM, the authors of [38] predicted the monthly electricity consumption for a year by using 3 years data to train the model.

Including weather data has also been found to support the prediction of a building’s energy consumption [39], [40]. The monthly average temperature was used in [41] to improve the accuracy of prediction of monthly power consumption of a building. Later, this approach was compared to the temperature frequency methods in [42]. In [43] the energy consumption for one season was predicted by considering many components like space heating, hot water usage etc. and by applying a specific model for each component. A feed forward ANN was used in [44] to predict the electricity consumption by relating the local weather and occupancy of the building. Another model used SVM to predict one year electricity consumption using weather variables [45].

Although considerable work has been done in using weather data in the process of forecasting the energy consumption of a building, filtering the weather data and identifying the optimal weather dataset in order to increase the accuracy of the model has not yet been discussed. In addition, the above models have never been combined to develop a “triad” prediction model in order to forecast the building's energy demand and the "triad" peak at the same time. The aims of this paper are:

1) To forecast the most probable day and most probably half hour on that day a "triad" could occur.

2) To identify the most dominant weather attributes which would improve the demand forecast.

3) To forecast the building's demand at the most probable "triad" day and half-hour.

3 Model Description

The proposed "Triad Demand Predictive Model" is presented in Figure 1 and consists of three sub-models, namely "Triad Probability Assessment" model, "Pre-Forecast Analysis" model and "Electricity Demand Forecast" model. Each of these sub-models performs different tasks using inputs from external sources or other sub-models.

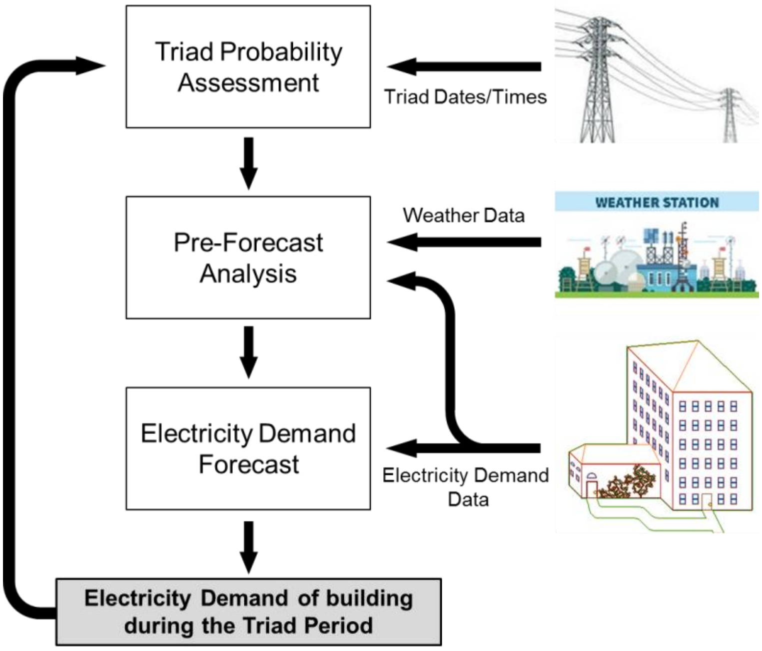

Figure 1: The forecasting model

3.1 Model Inputs

The predictive model uses data from three different sources at various stages to predict the most probable half hour of the day when the triad could occur. The data is fed into the model in three stages (one for each sub-model).

For the "Triad Probability Assessment" model 25 years of triad data were collected from National Grid (http://www2.nationalgrid.com/uk/) including information regarding the dates and times of the "triad" peaks of the corresponding years. These data were used in order to calculate the most probable dates and times of the triad peaks for the forthcoming year.

The second dataset consisted of weather data. Two years of weather data were obtained from the MetOffice (http://wow.metoffice.gov.uk/) to be used as an input to the "Pre-Forecast" model. The data contained information from the weather station near the building being considered over the period 2012-2013. Hourly information about the sunny hours, air temperature, rainfall, hourly global radiation, relative humidity, mean wind direction, wind mean speed, extent of cloud cover and wind gust in knots was available. The weather data was used for our analysis to improve the accuracy of the predictive model.

The third data input to the model was historical energy consumption data from commercial buildings. Half-hourly power demand data were available from six commercial buildings of a science park allowing the evaluation of the model on a realistic environment. The historical power demand data were used by both the "Pre-Forecast Analysis" model and the "Electricity Demand Forecast" model.

3.2 Triad Probability Assessment model

A stochastic model was developed to estimate the "triad" days for the forthcoming year. The model uses historical triad data (date and time) to calculate the probability of having a "triad" peak on certain dates during the "triad season". The most probable dates for a "triad" peak are calculated with configurable granularity, using intervals which have duration from 1 to 20 days. Assuming that there are 120 days between 1st of Nov and the end of February, setting the interval to -1- would result in 120 probability values (one for each day). In case the interval is set to -2-, the model produces 60 probability values (one for each 2-day period) etc. As seen in the next sections, reducing the forecasting resolution (by increasing the interval size) increases the forecasting accuracy. This trade-off between forecast resolution and forecast accuracy has to be determined by the model's operator based on the context of use, and it is out of the scope of this paper.

The probability *P(i)* of each interval *i* to include a "triad" peak is calculated using Equation (1) below:

$$P(i) = \frac{\sum_{n=1}^{N}\left(\sum_{k=1}^{3}\left(n \cdot \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{(i-T_n^{(k)})^2}{2\sigma^2}}\right)\right)}{\sum_{n=1}^{N} 3n} \tag{1}$$

where:

$P(i)$ is the probability of interval-i including a triad peak (if the interval is one day, $P(i)$ is the probability of that day being a triad one)
i is the interval index
n is the year index (N^{th} year is the most recent year)
N is the total number of years that triad data are available
k is the triad index for a year
σ is the standard deviation of the normal distribution (=1 in our model)
$T^{(k)}{}_n$ is the interval that includes the k^{th} triad peak of year n

As seen from Equation (1), the probability $P(i)$ of each interval i is obtained by superimposing a set of 3 normal distributions for each year for which triad data are available. These normal distributions have as mean value the index of the "triad" interval (the interval that includes a "triad" day in that year), and a standard deviation of 1. With this method, each "triad" date affects not only the probability of the same interval but also the probability of the neighbouring ones. Considering weekly intervals for example, if week 5 includes a "triad" date, its probability is increased but so is the probability of weeks 4, 6 and 3, 7 according to the normal distribution. This is done in order to consider the uncertainties introduced by the weather in the calculations. It is known that the "triad" dates are affected by the weather, e.g. it is more probable to have a "triad" peak when the mean temperature is low and the heating systems of the consumers are operating. By increasing the probability of the neighbouring intervals the model expresses the fuzzy relationship:

If the weather is cold $\Rightarrow$
We might have a "triad" peak

and interprets it in order to be used for a probabilistic assessment:

If we have had a "triad" peak in the past $\Rightarrow$
This period of the year has been cold $\Rightarrow$
This period and its neighbours might also be cold in the future $\Rightarrow$
We might have a "triad" peak on those periods in the future

According to [46], the assumption of normality is very common in models which deal with weather data. In addition, using normal distributions increases the generality of the model. A custom distribution specifically designed for a geographical area would reduce the applicability of the model and the accuracy of the results would be depended on the size of the dataset used to design the custom distribution. For these reasons the use of a normal distribution was considered suitable for this model.

The model is built with a learning feature which improves the probability assessment on an annual basis as new "triad" data becomes available. Emphasis is given to the most recent data, by including weights (n in Equation 1). In this way the model can detect possible changes in the pattern caused by external factors that change on an annual basis (e.g. weather, technology). A linear weight relationship was assumed for these factors – however, any prior knowledge that a user may have can be used to modify these weights. Finally, the sum of the weighted normal distribution is divided by the sum of weights n in order to obtain the probability $P(i)$ as a weighted average.

The model also calculates the most probable half-hours within a day during which the "triad" peak demand is expected to occur. Equation 1 is used in a different way to obtain the half-hourly probability of a "triad" peak in a day. In this case the intervals have a fixed duration of 30 minutes, so only 48 intervals are assessed for one day. The model looks only at the times that the "triad" peaks occurred, and tries to identify the most probable half-hours for one. The weather is not an important factor in this case. What is most important is the daily profile of electricity demand in the system. This profile is directly related to the activities of the customers and their energy consumption patterns. By superimposing normal distributions for each "triad" half-hour, we are able to identify an "alert" band, a set of intervals where the "triad" peaks are expected to appear. The interpreted relationship in this case is:

If we had a "triad" peak at this half hour in the past $\Rightarrow$
Electricity-demanding activities are happening at this time of day $\Rightarrow$
These activities could happen at this time and its neighbours in the future $\Rightarrow$
We might have a "triad" peak this time in the future

The model is able to detect possible changes on a daily basis, caused by changes in the daily patterns of the customer's consumption. This becomes particularly relevant as consumers of electricity become more proactive and aware of electricity tariffs, and shift their energy consumption at hours when the price/MWh is low. The increasing uptake of electric vehicles (EVs) will also have a significant effect on the daily patterns of a consumer [47]. According to [48]–[51], the charging demand patterns of EVs can change completely the electricity profile of a consumer. By including annual weights the model can detect these changes and update the probability assessment of the "triad" half-hours.

3.3 Pre-Forecast Analysis model

A Pre-Forecast Analysis model was developed in order to increase the performance of electricity demand estimation by including weather information in the forecasting process. The objective of this model is to identify the optimal number of weather attributes to be considered within the "Electricity Demand Forecast". To this end an iterative process is followed, as illustrated in Figure 2.

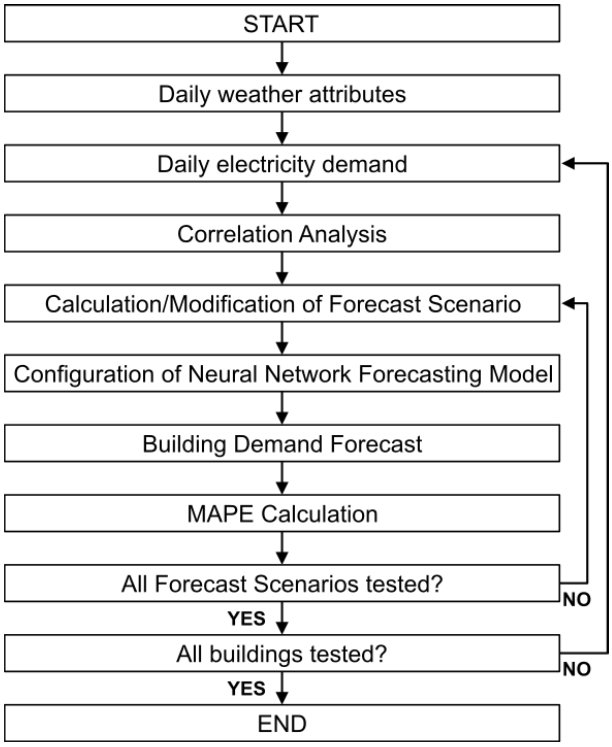

Figure 2: The Pre-Forecast Analysis flowchart

Using historical local weather data and building energy consumption data, a correlation analysis was performed in order to calculate the correlation of the available weather data with the electricity demand of each building. Pearson's correlation matrix was calculated in order to identify the attributes which have the highest correlation with the energy consumption of each building. Since buildings have different energy consumption profiles, the correlation matrix was calculated separately for each building.

Having the correlation matrix, a sensitivity analysis was performed in order to identify the optimal set of attributes to be considered in the forecast. A set of 11 “Forecast Scenarios” were defined for each building, consisting of different sets of attributes to be considered in the forecast. The base attributes were assumed to be the power demand, time, day and type of day (weekday/weekend). The considered scenarios and their corresponding attributes are listed below:

1. *No weather attributes:* Considering only the power demand, time, day and type of day (weekday/weekend)
2. *“y” weather attribute(s):* Considering the power demand, time, day, type of day (weekday/weekend) and the “y” most dominant weather attribute(s), i.e. attributes with the highest correlation factor. The index “y” varies from 1 to 10.

To identify the optimal forecast scenario, an ANN forecasting model was built using the WEKA toolkit [52] and a custom implementation, and the half-hourly electricity consumption on a random day was forecasted for each building. The data was divided into two datasets: the first dataset consisted of the first n-1 days and was used to train the model and the second dataset consisted of the n-th day in order to test the model.

A parametric study was performed to identify the best set of ANN hyper-parameters to use for each building. The parameters that were included in the parametric study are: number of hidden layers, number of neurons in a hidden layer, learning rate and momentum. A step-wise search approach was used and the results were evaluated using cross-validation. The values of the hyper-parameters tested were:

a. Number of Hidden Layers:
    1 - number of additional attributes (steps of 1)

b. Number of neurons in hidden layer:
    total number of attributes – 2x total number of attributes – 3x total number of attributes

c. Learning Rate:
    0.3 - 0.6 - 0.9

d. Momentum:
    0.2 – 0.4 – 0.6 – 0.8

It was found that the best results were achieved when the number of hidden layers matched the number of additional attributes considered during the training/testing phase, the number of neurons in a layer matches the total number of attributes, the learning rate has a value of 0.3 and the momentum has a value of 0.2. The transfer function used is Sigmoid. Other functions were also tested (TanH and ReLu) and gave similar results.

The forecast accuracy for each scenario was calculated using the mean absolute percentage error (MAPE) and the Mean Absolute Error (MAE) index. For each building the attribute set (forecast scenario) that resulted in the least errors was selected as the optimal one for the electricity demand forecast.

3.4 Electricity Demand Forecast model

The third sub-model is the "Electricity Demand Forecast" model. In this model the outputs of the previous sub-models were combined in order to forecast the electricity demand of the building on a "triad" peak period considering the optimal set of weather attributes. The model performs a day-ahead power demand forecast using the optimal ANN configuration suggested by the "Pre-Forecast Analysis" model.

The ANN technique was selected after comparing five techniques, namely Linear Regression, Instance-based learning (K*), Support Vector Regression, Multi-Layer Perceptron ANN and Decision Trees. Each technique was trained and tested on the same dataset using the default parameters of WEKA toolkit and a custom ANN implementation. The results are presented in Table I:

Table I: Mean Absolute Error for every technique

	Linear Regression	Instance-based learning (K*)	Support Vector Regression	MLP ANN	Decision Trees
Building 1	10.61	15.07	9.68	6.24	6.68
Building 2	9.10	10.43	9.81	4.58	4.74
Building 3	1.94	2.14	1.86	1.09	1.10
Building 4	2.05	1.41	2.19	0.81	0.78
Building 5	34.63	35.25	37.28	24.47	29.61
Building 6	3.51	3.16	2.67	3.04	2.51
Average MAE	10.31	11.24	10.58	6.70	7.57

As observed from Table I, the ANN had an overall better performance than the other techniques for our dataset. The following algorithm describes the model's operation for the considered 6 buildings:

Algorithm 1: Algorithm of the "Electricity Demand Forecast" model

Input: Most probable triad days and half hours, optimal forecast scenario
Output: Building power demand during a triad half hour

Select the most probable days triad and half hours on that day as calculated from Triad Probability Assessment model;
$i = 1$;
while $i \leq 6$ **do**
    Configure the ANN according to the output of the Pre-Forecast Analysis model for building-i;
    Build the training and the testing dataset;
    Train the model;
    Forecast the power demand of building-i for the half hour that a triad is most likely to happen;
    $i = i + 1$

Algorithm 1 describes the process of forecasting the power demand for the most probable half hour of a triad day for the 6 buildings. Two inputs are required for this. The first is the period identified as the most probable periods for a "triad" peak (output of the "Triad Probability Assessment" model). The second input is the forecast scenario of the "Pre-Forecast Analysis" model that gives the lowest MAPE for each building. Having these inputs from the previous sub-models, the "Electricity Demand Forecast" model uses an iterative loop and performs a power demand forecast for each building. Inside this loop, the ANN parameters are set based on the forecast scenario identified in the "Pre-Forecast Analysis" model. Once the ANN is configured, the training and testing files are built according to the optimal forecast scenario. The ANN is different for each building, as it may follow a different forecast scenario. At the end of this iterative process, the power demand for each building is calculated for the most probable triad half-hour. This demand forecast gives the building manager a pre-emptive advantage to reduce their energy bills by using various control methods to decrease the consumption of its buildings.

4 Model Results

4.1 Triad Probability Assessment

The model was developed in Matlab and trained on real "triad" data from the period 1990 – 2014. The data was obtained from National Grid and included information regarding the dates and times of the "triad" peaks of the corresponding years. As mentioned before, intervals were defined to calculate the probability of the "triad" dates. Figures 3 and 4 present the results when considering intervals of 1-day and 5-days respectively. It is assumed that the building manager can define a warning threshold as a parameter for the model, and gets warnings for periods that are calculated to have a "triad" peak probability greater than a this threshold. In this case this threshold is assumed to be 70% of the maximum calculated probability over all intervals (the building manager will be warned for periods which are at the top 30% of the results).

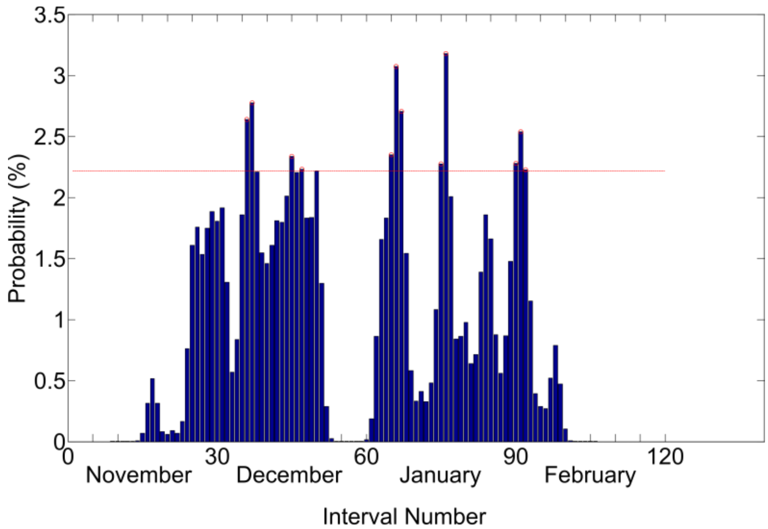

Figure 3: The daily probability distribution for "triad" peaks

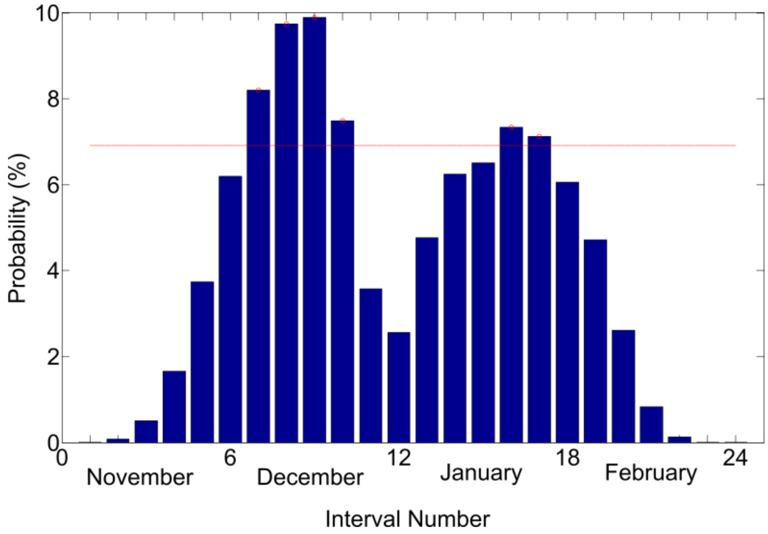

Figure 4: The 5-days probability distribution for "triad" peaks

As illustrated in Figure 3, the most probable "triad" intervals for 2014-2015 (the ones above the threshold) were calculated to be the following 12 days:

6th, 7th, 15th and 17th of December 2014
5th, 6th, 7th, 15th, 16th and 31th of January 2015
1st and 2nd of February 2015

From Figure 4, when the interval duration is increased to 5-days, the most probable dates for a "triad" peak are the following 30 days:

The first 4 intervals of December 2014 (1st – 20th of December)
The 4th and 5th intervals of January 2015 (16th – 25th of January)

As seen from the results, an increase in the duration of the interval results in more "relaxed" probability distributions. This is expected, as explained in the previous sections, since the effect of one "triad" peak on its neighbouring dates expands at longer interval durations. This results in having longer periods above the defined threshold, and consequently a greater number of "triad" warnings being generated.

It is important to more accurately specify both the interval duration and the warning threshold correctly. Assuming that a "triad" warning triggers demand reduction actions, the number of warnings is associated with other aspects of building use – such as the comfort of the building's occupants. The calculation of these costs (associated with building use) is out of the scope of this paper. The objective is to provide a tool to the building manager to calculate the probability of "triad" peaks. The building manager must carefully consider the overall impact associated with demand reduction actions on the building facility, and decide the optimal number of warnings for each particular case.

The model was also used to calculate the most probable half-hours for a "triad" peak in a day. As mentioned before, the interval duration was fixed to 30 minutes and the probability of each of 48 intervals in a day was assessed. The results are shown in Figure 5.

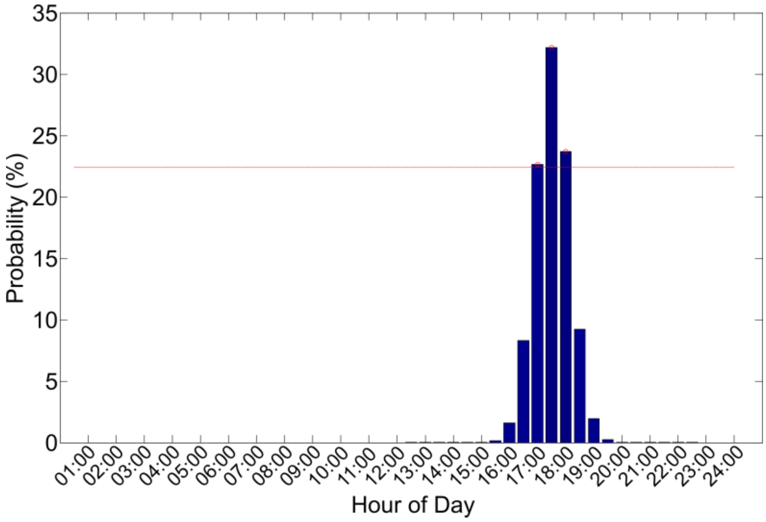

Figure 5: The half-hourly probability distribution for "triad" peaks

Assuming the same warning threshold as before, the most probable half-hour for a "triad" peak was calculated to be between 17:00 - 17:30. An "alert" band between 16:30 – 18:00 is clearly demonstrated. Using the model to calculate the probability of each half-hour of a day offers a number of advantages to the building manager. By identifying the exact half-hours for a "triad" peak, the duration of the demand reduction actions are limited and consequently so is the disruption of the occupants' use of the building. Reducing the need for long response periods reduces the overall risk of "missing" a triad peak, as the building managers will be able to increase the number of "triad" warnings they can respond to.

4.2 Pre-Forecast Analysis

The "Pre-Forecast Analysis" model was applied on data from the period of 2012-2013. Half-hourly energy consumption data from six commercial buildings (within a science park in the UK) were analysed and correlated with the corresponding local weather information. Pearson's correlation matrix associated with this data is presented in Table II.

Table II: Correlation matrix of energy consumption with weather data for the six buildings

Building	Cloud Total Amount Octas	Cloud Base Dm	Wind Mean Speed Knots	Hourly Mean Wind Dir	Max Gust Knots	Air Temp Deg C	Rainfall Mm	Hourly Glob Rad kjm2	Rh Hourly	Sun Hours
Building 1	3.52	5.42	0.06	5.95	1.33	1.91	3.53	3.23	0.45	8.78
Building 2	12.65	8.11	3.91	17.74	2.51	36.53	2.32	30.79	6.28	22.43
Building 3	11.70	7.11	15.69	7.17	16.60	35.11	5.91	20.22	2.05	13.73
Building 4	13.35	9.12	6.57	13.95	5.61	34.14	2.02	33.05	11.80	23.33
Building 5	15.08	7.62	7.09	12.51	7.35	46.30	2.30	45.14	17.99	24.41
Building 6	22.18	17.16	7.11	14.40	7.21	59.83	2.13	67.05	31.23	40.60

As seen from Table II, the correlation of energy consumption with the local weather is different for each building. The strength of these correlations can be extracted from the magnitudes of Pearson's correlation coefficients in this table (bigger is stronger). The weather attribute with the highest correlation to the demand of Building 1 was the number of hours of sunshine. For the Buildings 2-5 the attribute with the highest correlation was the outside air temperature. Lastly for Building 6 the attribute with highest correlation was that of hourly global radiation. As each building has a different structural architecture, area and occupancy, it normal to respond differently to the different weather attributes.

The purpose of this "Pre-Forecast Analysis" model is to identify the optimal combination of weather attributes to include in the "Electricity Demand Forecast" model. To this end, a number of forecasting scenarios were identified and their contribution to the forecast accuracy was calculated using the MAPE and the MAE index. This way, a weather sensitivity analysis was performed, testing each forecasting scenario and determining the number of hidden layers in the ANN to be used for each building. The results are presented in Figure 6 and Figure 7.

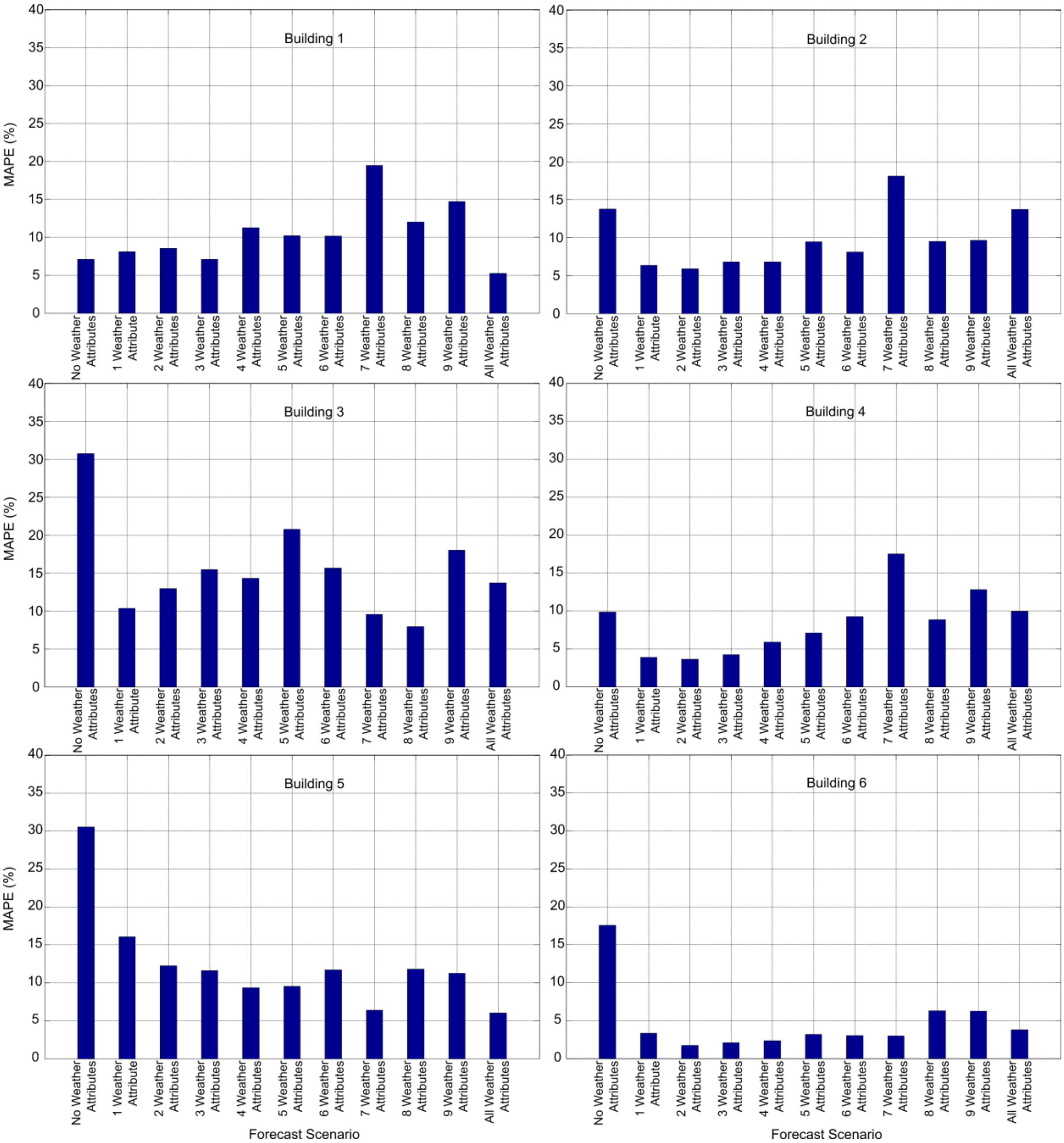

Figure 6: Weather sensitivity analysis for all buildings (MAPE index)

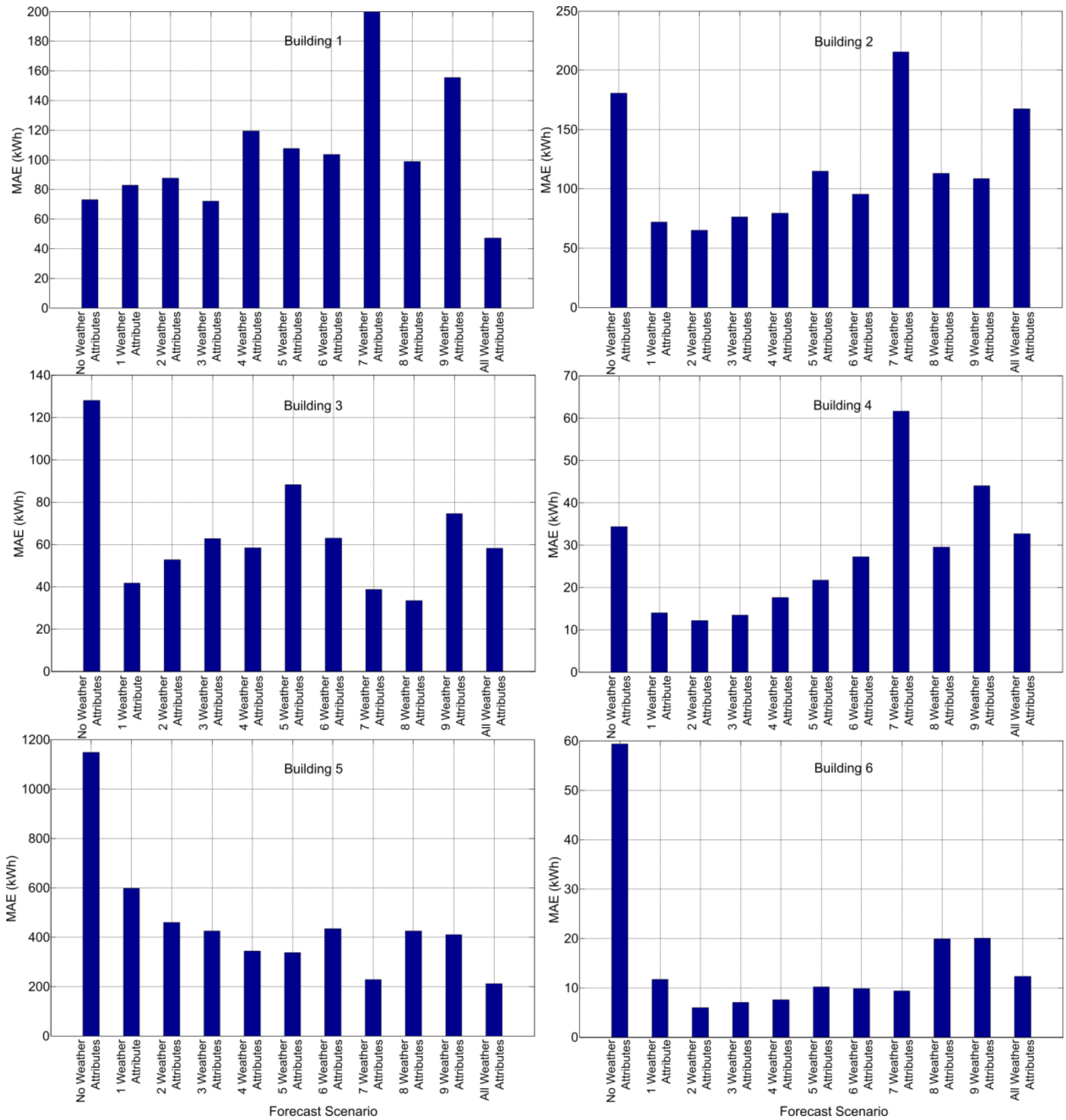

Figure 7: Weather sensitivity analysis for all buildings (MAE index)

For Building 1 the forecast MAPE without considering any weather attributes was around 7% and when the most dominant weather attribute (sunny hours) was considered in the forecasting model the MAPE increased to 8%. After running all forecast scenarios, the lowest MAPE was found when considering all the weather attributes in the forecasting model (last scenario). Based on this, the ANN to be used in the "Electricity Demand Forecast" model for Building 1 needs to consider all weather attributes and use 14 hidden layers (same as the number of the attributes considered in the last scenario).

The electricity demand forecast for Building 2 without considering any weather attributes resulted in a MAPE of 13%. This was reduced to 6.4% when the outside air temperature was added to the training and testing file. The MAPE was further reduced to 5.8% when the top two correlated weather attributes (outside air temperature and hourly global radiation) were added to the training and testing file. Unlike the forecast results of Building 1 which had the lowest MAPE when considering all weather attributes, for Building 2 the MAPE remained higher than 5.8% as the number of considered weather attributes was increased. According to this, the ANN of the "Electricity Demand Forecast" model for Building 2 needs to consider two weather attributes (outside air temperature and hourly global radiation) and use 6 hidden layers.

With Building 3, the daily forecasting model gave a MAPE of 30% when the demand was forecasted without considering any weather attributes. It was reduced substantially when weather attributes were added to the training procedure, and a minimum MAPE of around 7% was reached when considering the 8 most dominant weather attributes. Based on these findings the ANN of the "Electricity Demand Forecast" model for Building 3 was configured to use 12 hidden layers and the top 8 weather attributes.

Building 4 had similar results to Building 2, although at a smaller magnitude. In this case, the lowest MAPE was recorded when considering the two strongest weather attributes and the ANN of the "Electricity Demand Forecast" model for Building 4 was configured to use 6 hidden layers.

The forecasting error reduction when considering weather attributes was very large for Building 5. A quite high MAPE (around 30%) was found when the forecast was done without considering any weather attributes. This number reduced to 6% when considering all the weather attributes, and 14 hidden layers were used in the ANN of the "Electricity Demand Forecast" model for this building.

The smallest forecast errors were found for Building 6. Despite the MAPE was greater than 15% in the No Weather Attributes scenario, in almost all the forecast scenarios which considered some weather attributes the MAPE were reduced to below 5%. A maximum MAPE reduction of 88% was found when considering the two most dominant weather attributes for this building, and consequently the ANN of the "Electricity Demand Forecast" model for Building 6 was configured to use 6 hidden layers.

As seen from this analysis, considering weather information when forecasting the electricity demand of a building reduces the forecasting errors. Furthermore, by choosing the correct weather attributes to be considered in the forecasting process, results in removing the irrelevant and "noisy" data and increases the forecast accuracy.

4.3 Electricity Demand Forecast

The power demand at 17:30 of the 6th of December 2013 (actual triad half hour and day) was forecasted separately for each building. The findings of the "Pre-Forecast Analysis" model were used in order to consider the optimal combination of weather attributes and configure the ANN for each building separately. The forecasted demand for each building is presented in Figure 8.

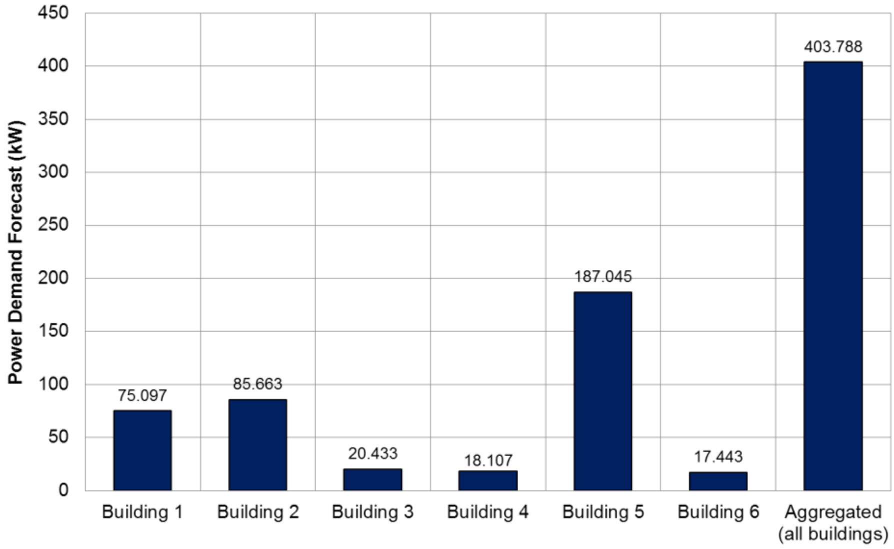

Figure 8: Electricity demand forecast for all buildings

5 Model Validation

To validate the proposed model, the results were compared with the actual triad dates and times as well as the actual electricity demand of each building on the forecasted day and half-hour. The actual "triad" dates for 2014/2015 are presented in Table III:

Table III: The actual "triad" peak dates and times of 2014/2015

Triad Date	Triad Half-Hour
4th of December 2014	17:00 – 17:30
19th of January 2015	17:00 – 17:30
2nd of February 2015	17:30 – 18:00

To compare the results of the "Triad Probability Assessment Model" to the actual "triad" dates for 2014/2015, Figures 9-11 present the actual dates/times with red colour.

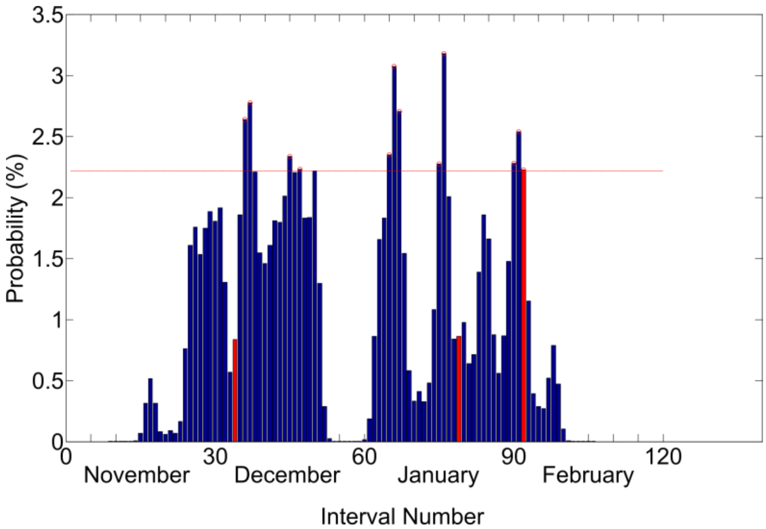

Figure 9: The actual “triad” peak days of 2014/2015 compared to the calculated daily probability distribution

As illustrated in Figure 9, one “triad” peak was above the warning threshold when considering daily intervals for the calculations. The results are considered satisfactory, bearing in mind that the “triad” peak of December was only missed for two days.

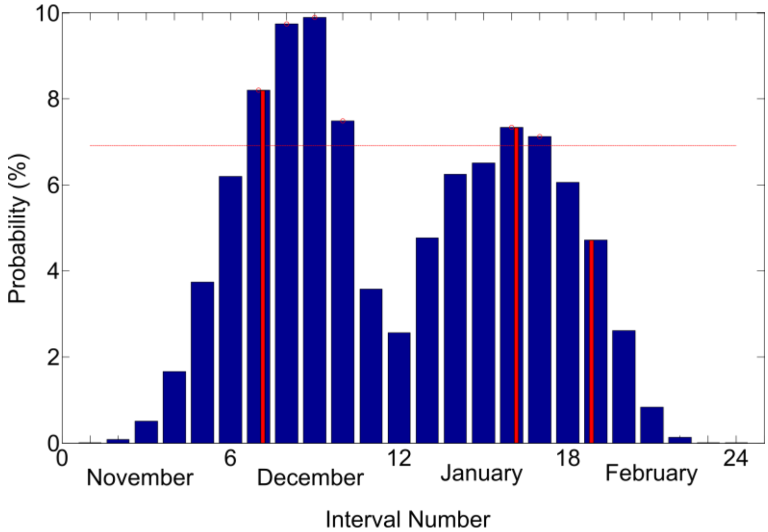

Figure 10: The actual “triad” peak days of 2014/2015 compared to the calculated 5-day probability distribution

From Figure 10, when the interval duration was increased to 5 days, the “Triad Probability Assessment” model was able to predict two “triad” peaks in the same year. As explained previously however, an increase in the duration of the intervals results in a large number of “triad” warnings (30 compared to 12). This is something which should be carefully considered by the building manager.

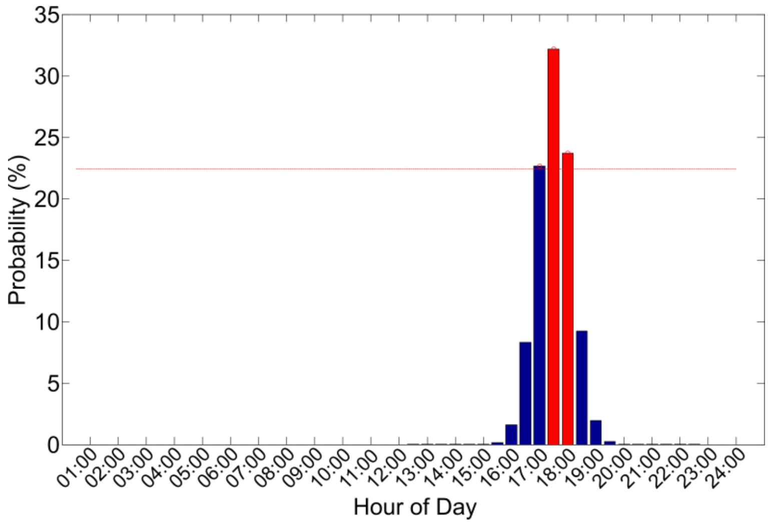

Figure 11: The actual “triad” peak half-hours of 2014/2015 compared to the calculated half-hourly probability distribution

Figure 11 presents the actual "triad" peak half-hours of 2014/2015 compared to the calculated half-hourly probability distribution. As seen from Table III, two "triad" peaks occurred between 17:00 and 17:30, while the third one occurred between 17:30 and 18:00. The "Triad Probability Assessment" model calculated the period between 16:30 and 18:00 to be the most probable for a "triad" peak which was correct for all three "triad" peaks. The model has a high accuracy, as warnings were issued for all "triad" half-hours. Having an accurate prediction of the exact "triad" half-hours, the building managers are able to avoid the "triad" peaks and reduce their operational costs. Furthermore, the fact that the "alert" zone is only 1.5 hours long reduces any other costs generated when reducing a building's usage profile (e.g. the cost of the occupants' discomfort).

To validate the "Pre-Forecast Analysis" and the "Electricity Demand Forecast" models, the forecasted power demand for each building was compared to the actual one. Figure 12 presents the forecasted and actual power demand for all buildings, while Figure 13 presents the forecasting percentage errors in each case.

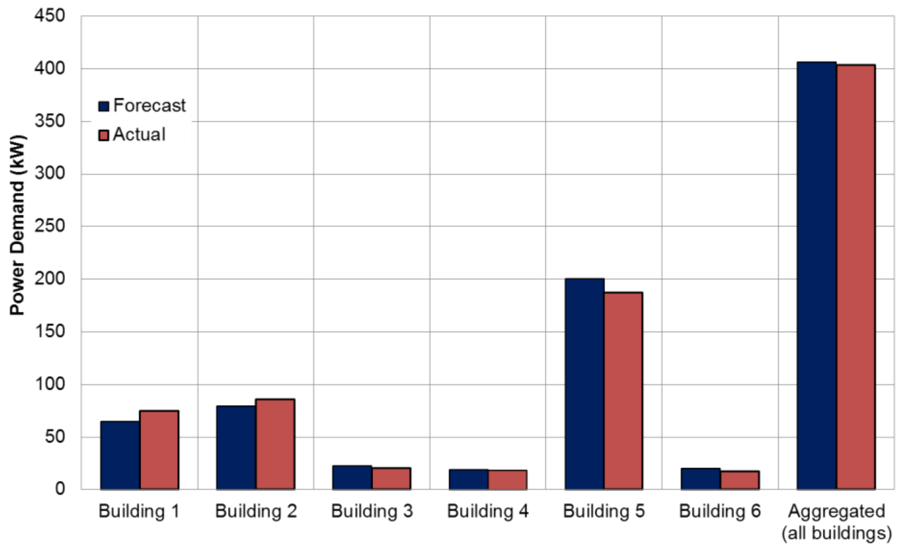

Figure 12: Forecasted and actual power demand for all buildings

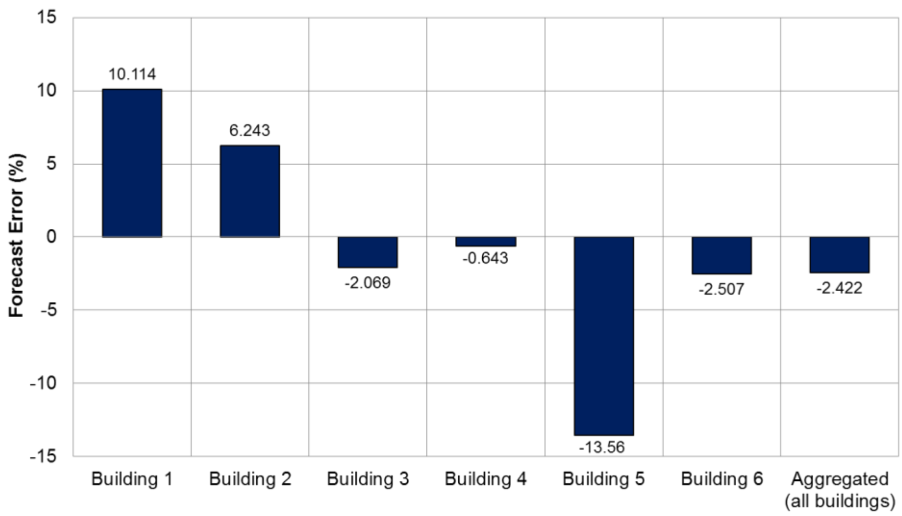

Figure 13: Error of power demand forecast for all buildings

As seen from Figures 12-13, the maximum error was found to be -13.56% for Building 5. Three forecasts had errors less than 3% which are considered very accurate, while the accuracy of the other three was found above 89%. Buildings 1 and 5 have errors larger than 10%. In these cases additional attributes are necessary to be included in the forecast model (e.g. occupancy, working hours, utility) to increase the prediction accuracy. However this is out of the scope of this paper.

This model aims to assist the building manager in estimating the triad days/hours and forecast the electricity demand of the facility. What may also be useful for a building manager is the aggregated electricity demand of the facility (all buildings combined). As seen from Figure 13, the error when aggregating the forecasts from each building is -2.422%. As individual errors can be positive or negative (the demand was overestimated in some buildings and underestimated in others), their aggregation results in a smaller error. Furthermore, having both negative and positive errors proves that the forecast errors are not systematic and the proposed forecasting model is unbiased.

6 Conclusions

A Triad Demand Predictive model was developed to forecast the power demand of commercial buildings during the “triad” periods. The model calculates the probability of having a “triad” on a daily and half-hourly basis and predicts the power demand of the building at the periods when a “triad” peak is more likely to occur. A Pre-Forecast stage was considered where the performance of the forecasting model was improved by considering weather attributes in the forecasting procedure. The model was validated using real UK data including “triad” dates and times, weather and building energy consumption information.

The model predicted successfully the dates of the two out of three “triad” peaks of 2014/2015. It was also found that reducing the granularity of the calculations can increase the prediction accuracy. In this case the building managers have to be flexible with their energy requirements and respond to a larger number of triad warnings.

The times of all three “triad” peaks were predicted successfully. We show that the “triad” peaks tend to occur over a relatively narrow time interval during a day (between 16:30 and 18:30). The building managers can use this information and adjust their demand profiles in order to reduce their costs.

The aggregated power demand of the building facility during an actual “triad” peak was predicted with 97.6% accuracy. We show that weather information plays a significant role in the accuracy of the building energy demand forecast. It was demonstrated that the choice of weather attributes is very important to forecast accuracy, and in some cases, using less weather data is more valuable and can lead to more accurate predictions.

To ensure that the outcome presented here is replicable, more data is needed to further generalise the findings reported. A diverse set of data from other geographical areas should be considered to capture the effect of local weather on forecasting the electricity demand of a building. Other types of buildings should also be analysed (e.g. industrial) to demonstrate how the proposed approach can be applied in a factory/industrial context. The configuration of ANN presented in this paper is not optimal for every dataset. Different ANN configurations should be tried and evaluated when analysing different datasets.

Acknowledgements

The authors would like to acknowledge the EPSRC project "Ebbs and Flows of Energy Systems" (EP/M507131/1) for supporting this work.

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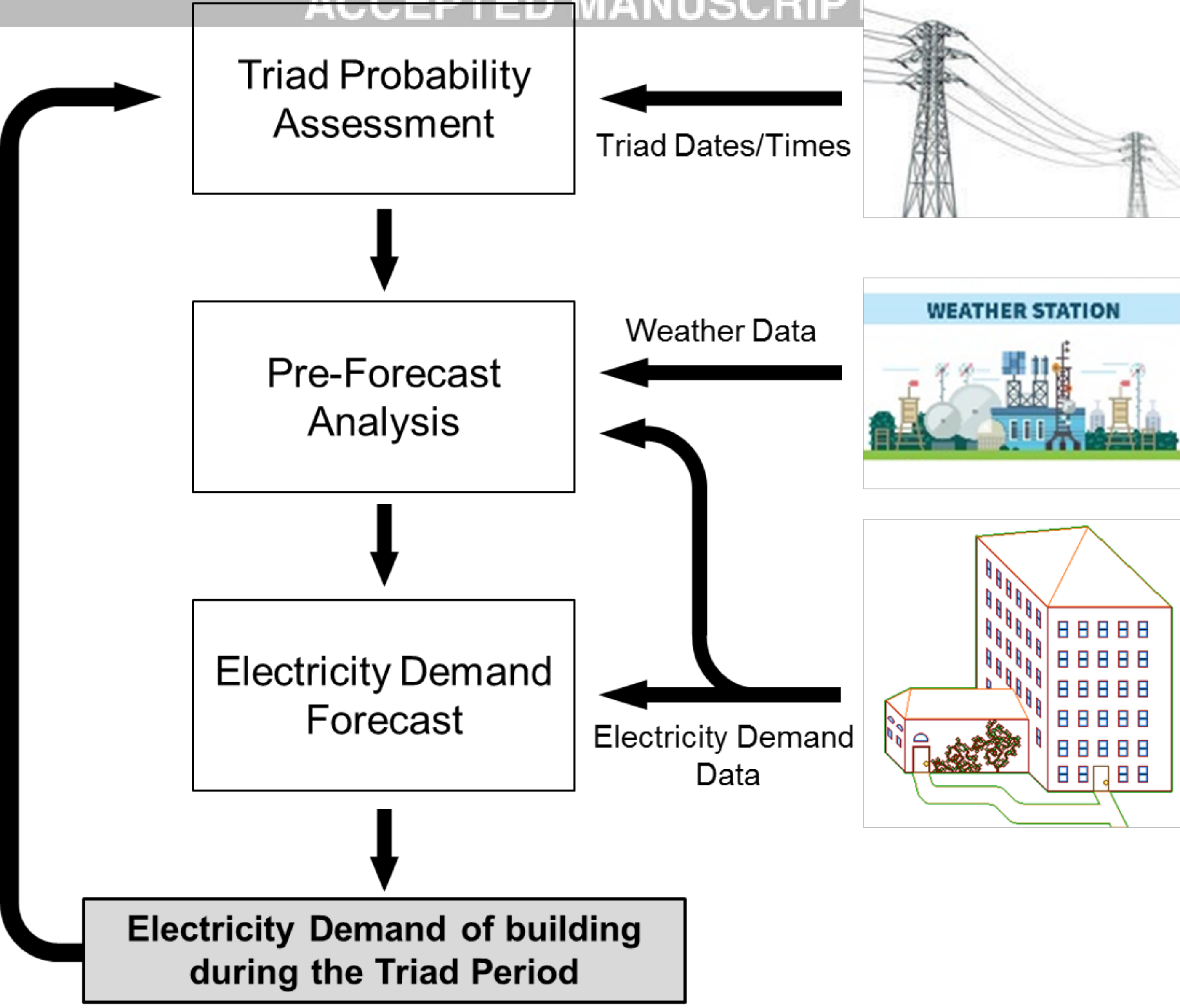
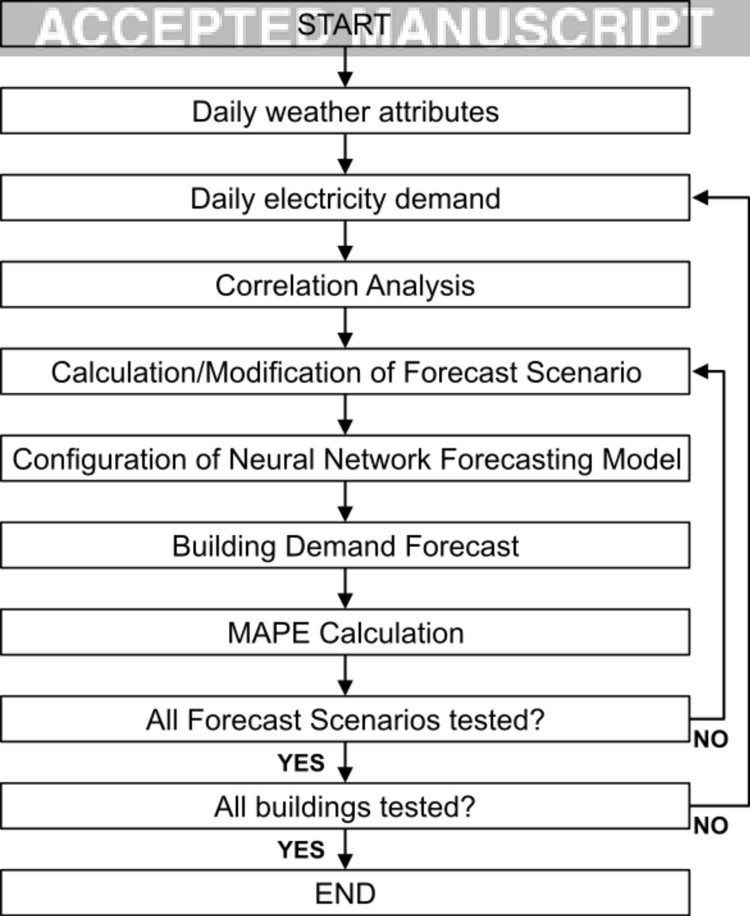

Triad Probability Assessment
Triad Dates/Times
Weather Data
WEATHER STATION
Pre-Forecast Analysis
Electricity Demand Forecast
Electricity Demand Data
Electricity Demand of building during the Triad Period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Daily electricity demand
Correlation Analysis
Calculation/Modification of Forecast Scenario
Configuration of Neural Network Forecasting Model
Building Demand Forecast
MAPE Calculation
All Forecast Scenarios tested?
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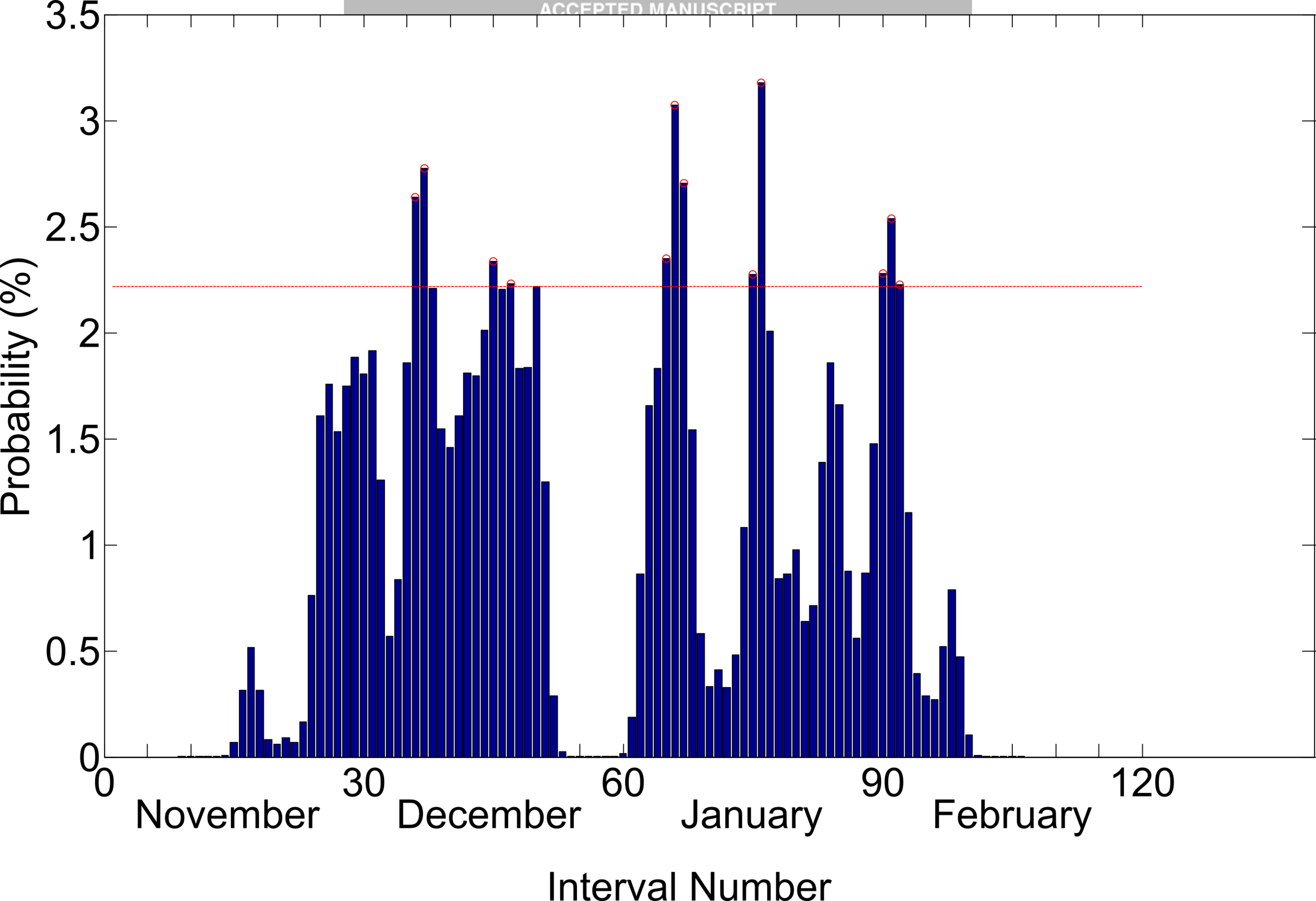
YES
All buildings tested?
NO
YES
END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2.5
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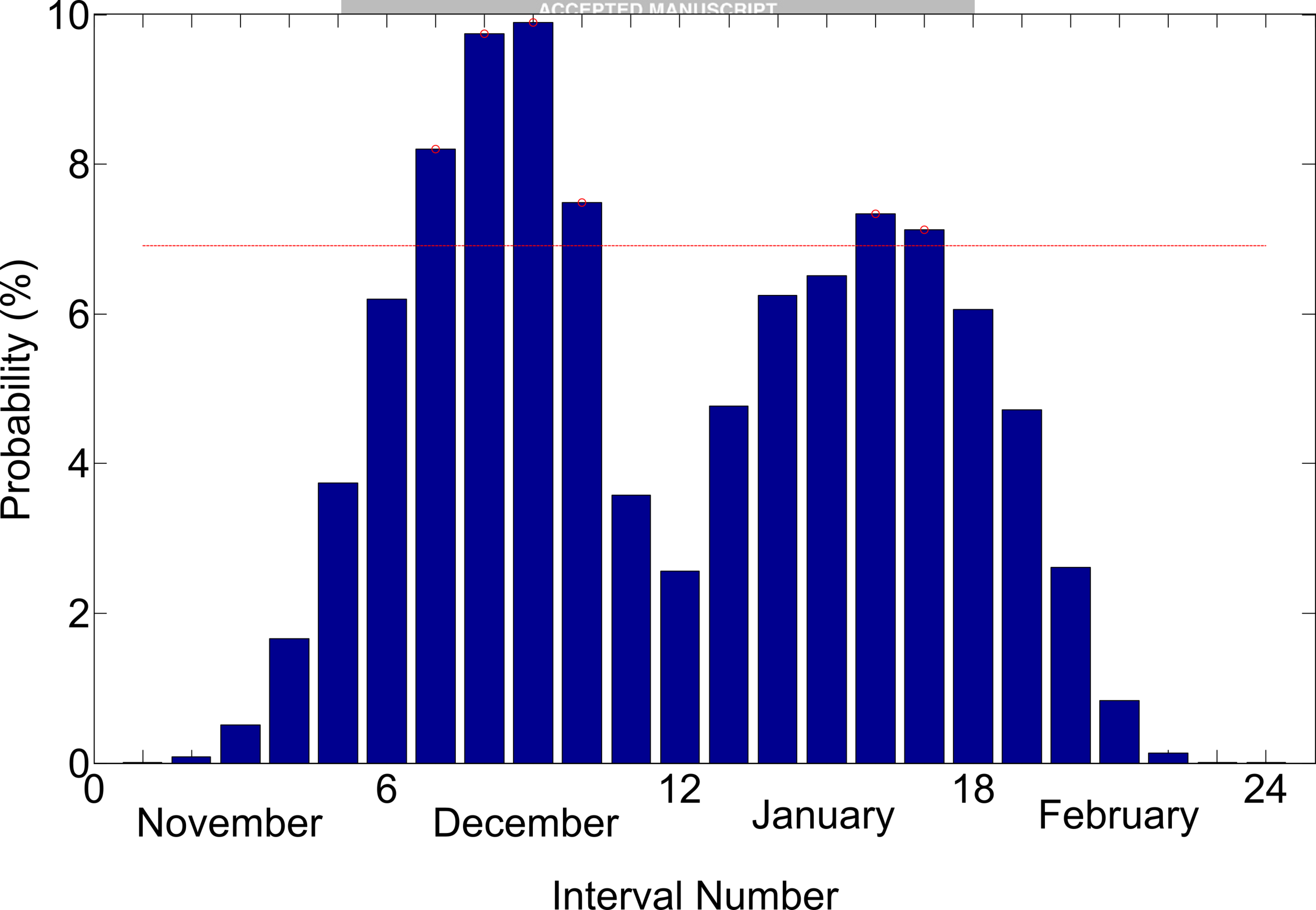
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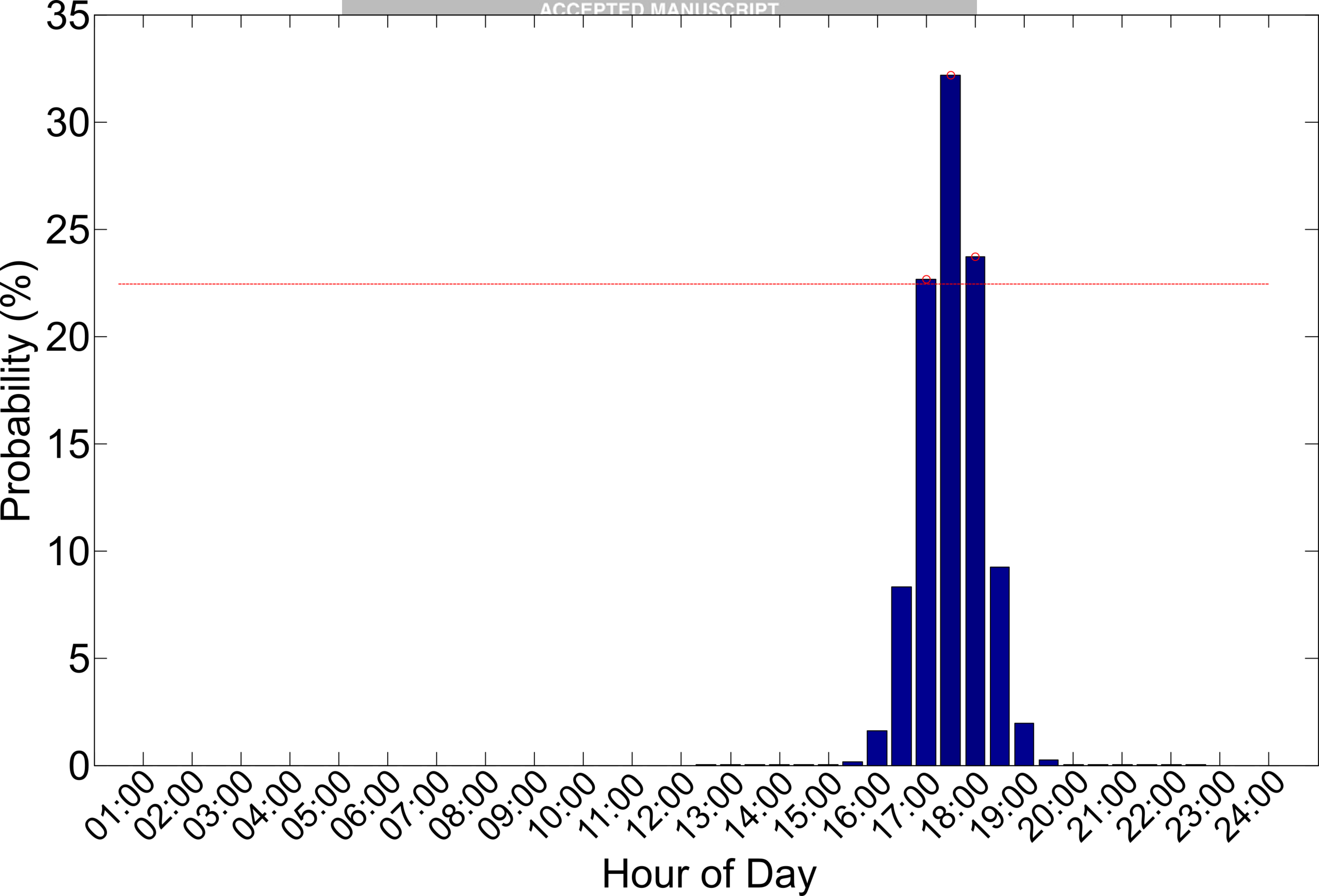

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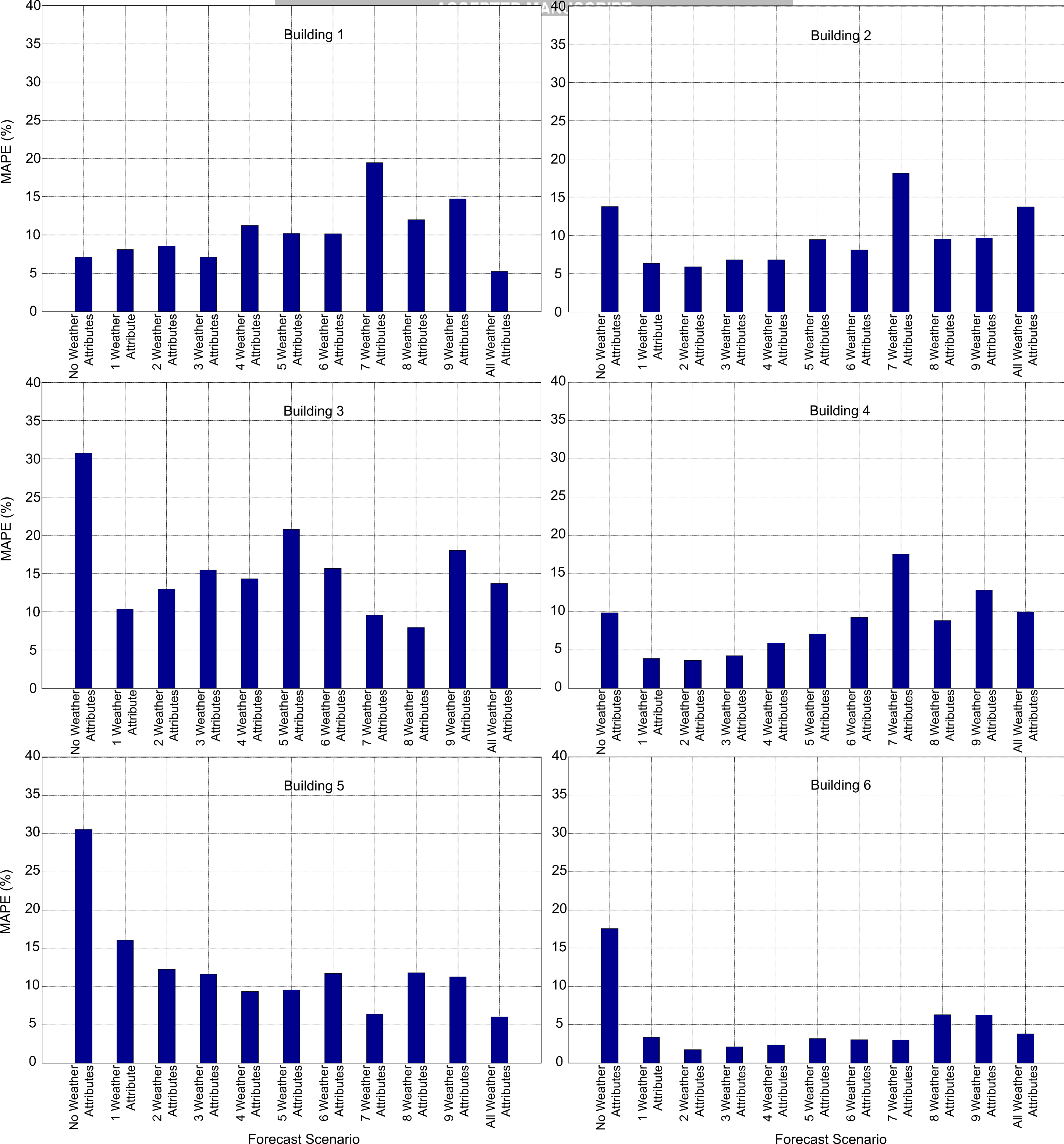
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Building 2
Building 3
Building 4
Building 5
Building 6
MAPE (%)
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1 Weather Attribute
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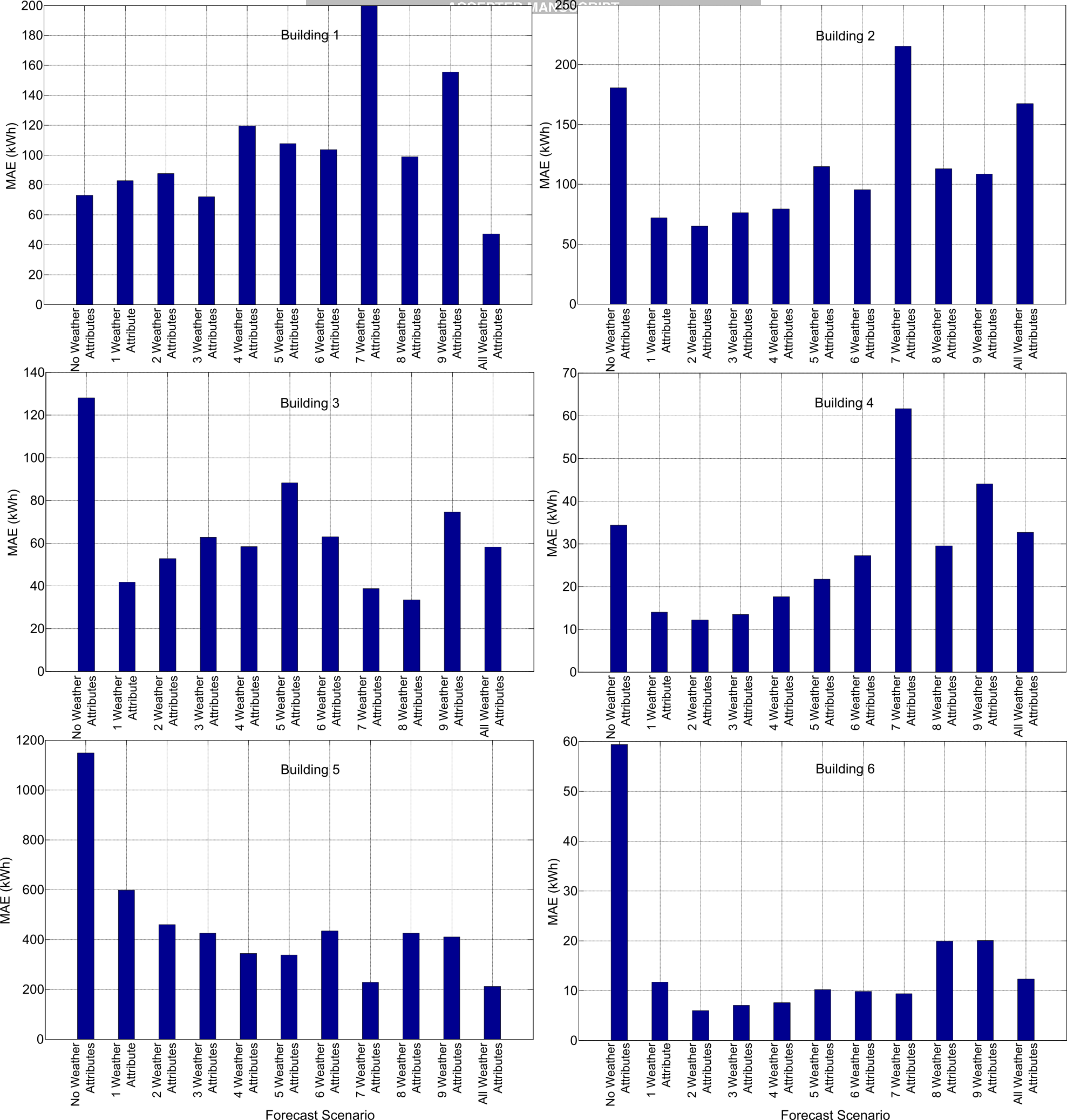
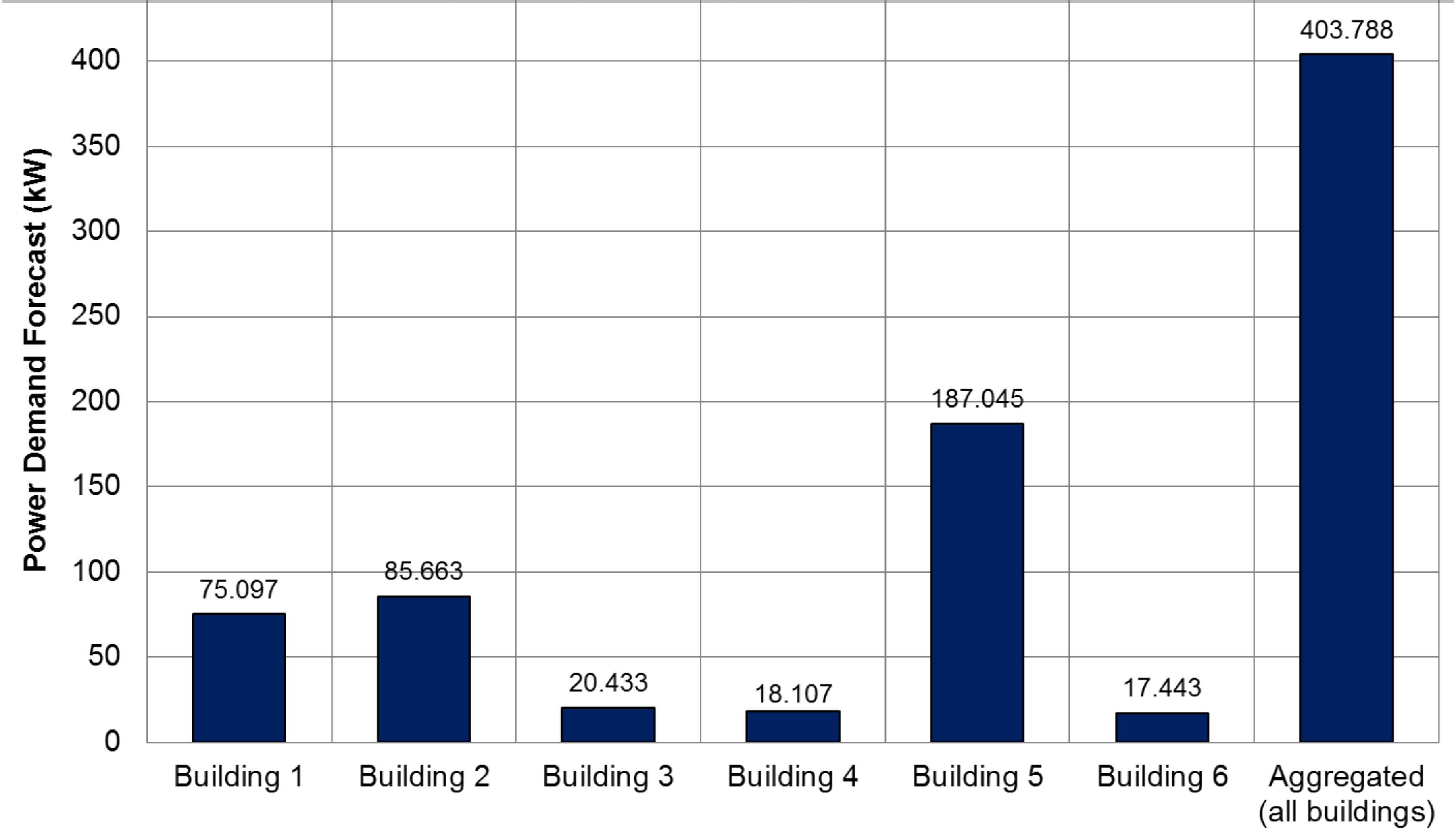
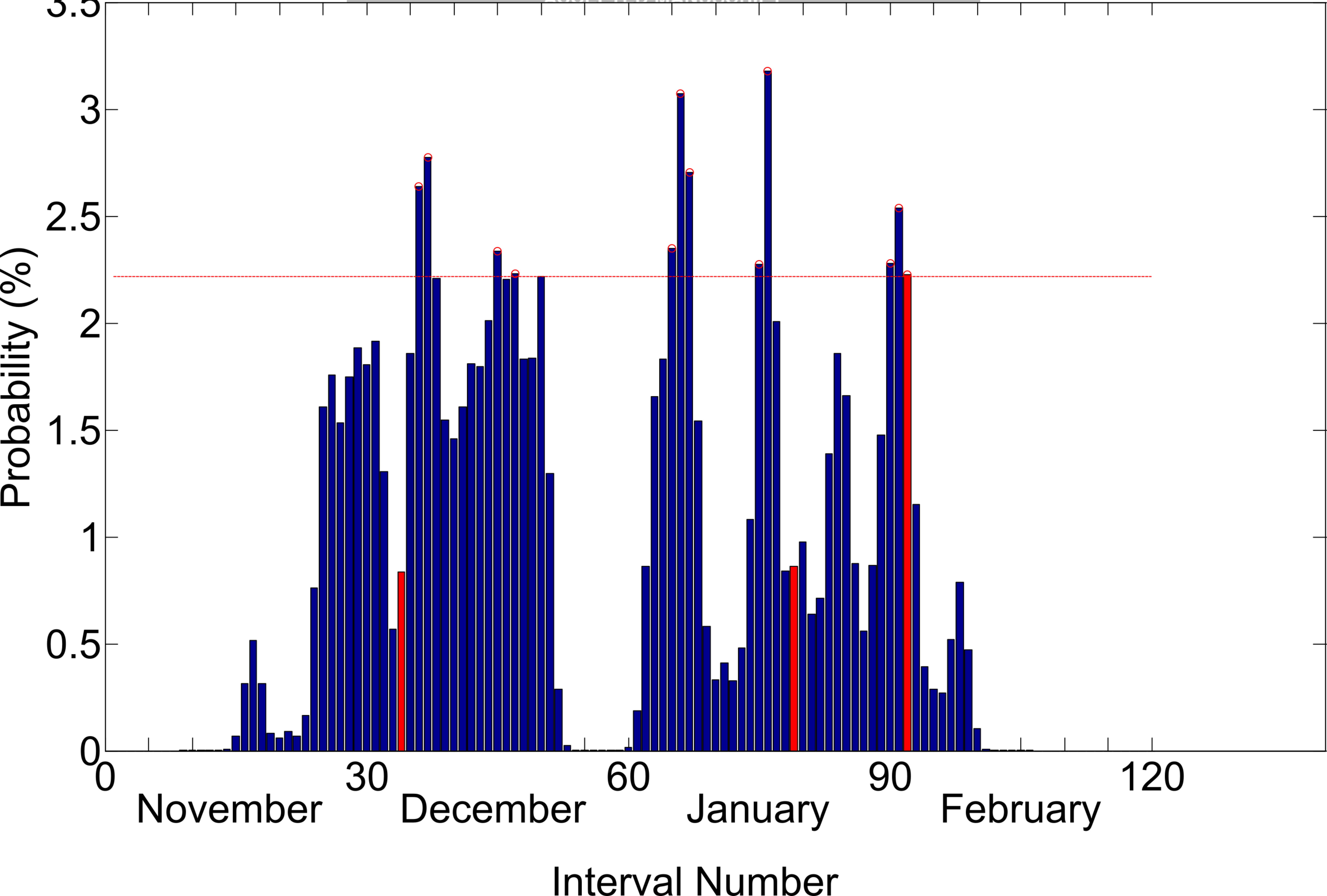
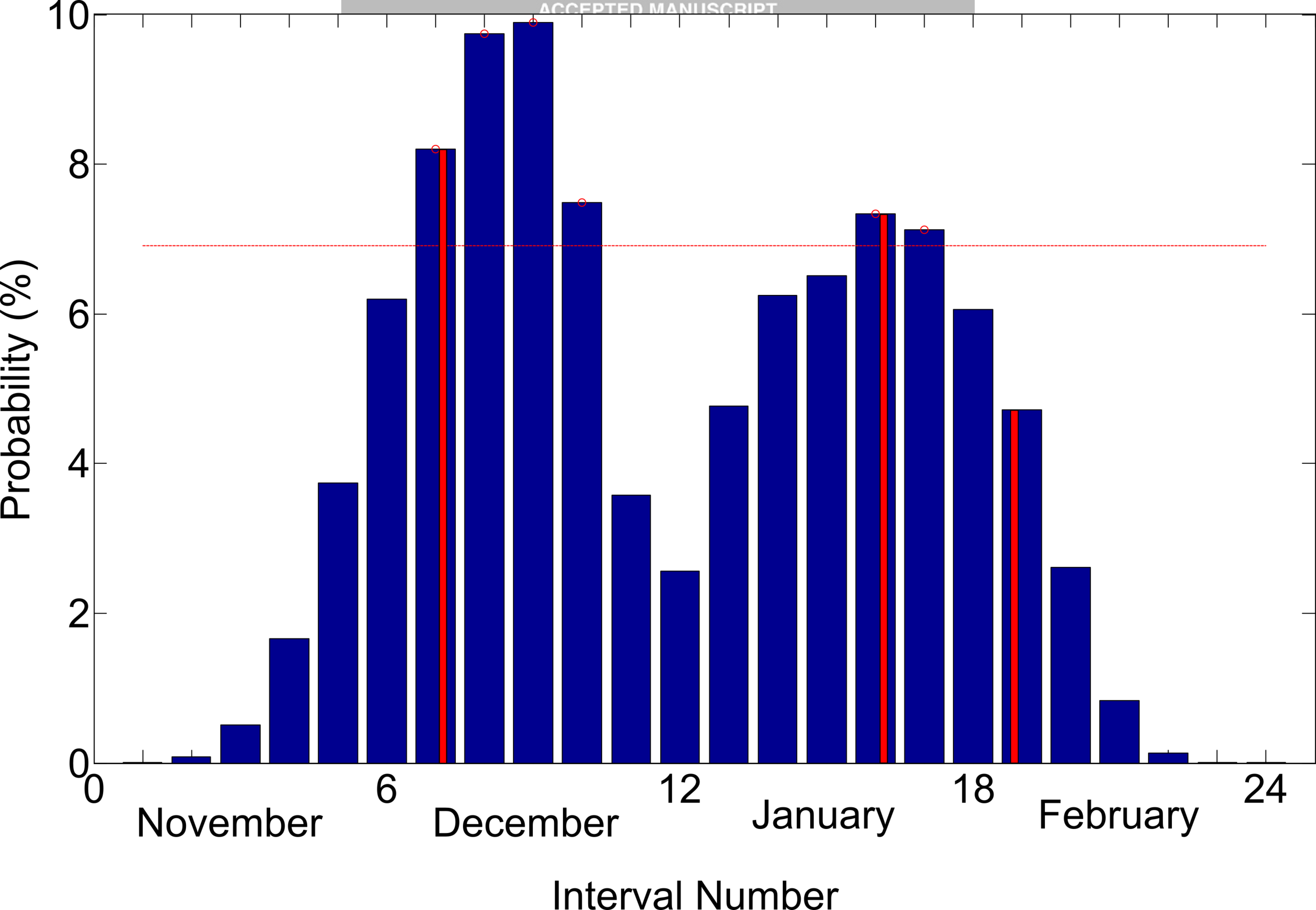
3 Weather Attributes
4 Weather Attributes
5 Weather Attributes
6 Weather Attributes
7 Weather Attributes
8 Weather Attributes
9 Weather Attributes
All Weather Attributes
Forecast Scenario


Building 1
Building 2
Building 3
Building 4
Building 5
Building 6
MAE (kWh)
Forecast Scenario
No Weather Attributes
1 Weather Attribute
2 Weather Attributes
3 Weather Attributes
4 Weather Attributes
5 Weather Attributes
6 Weather Attributes
7 Weather Attributes
8 Weather Attributes
9 Weather Attributes
All Weather Attributes

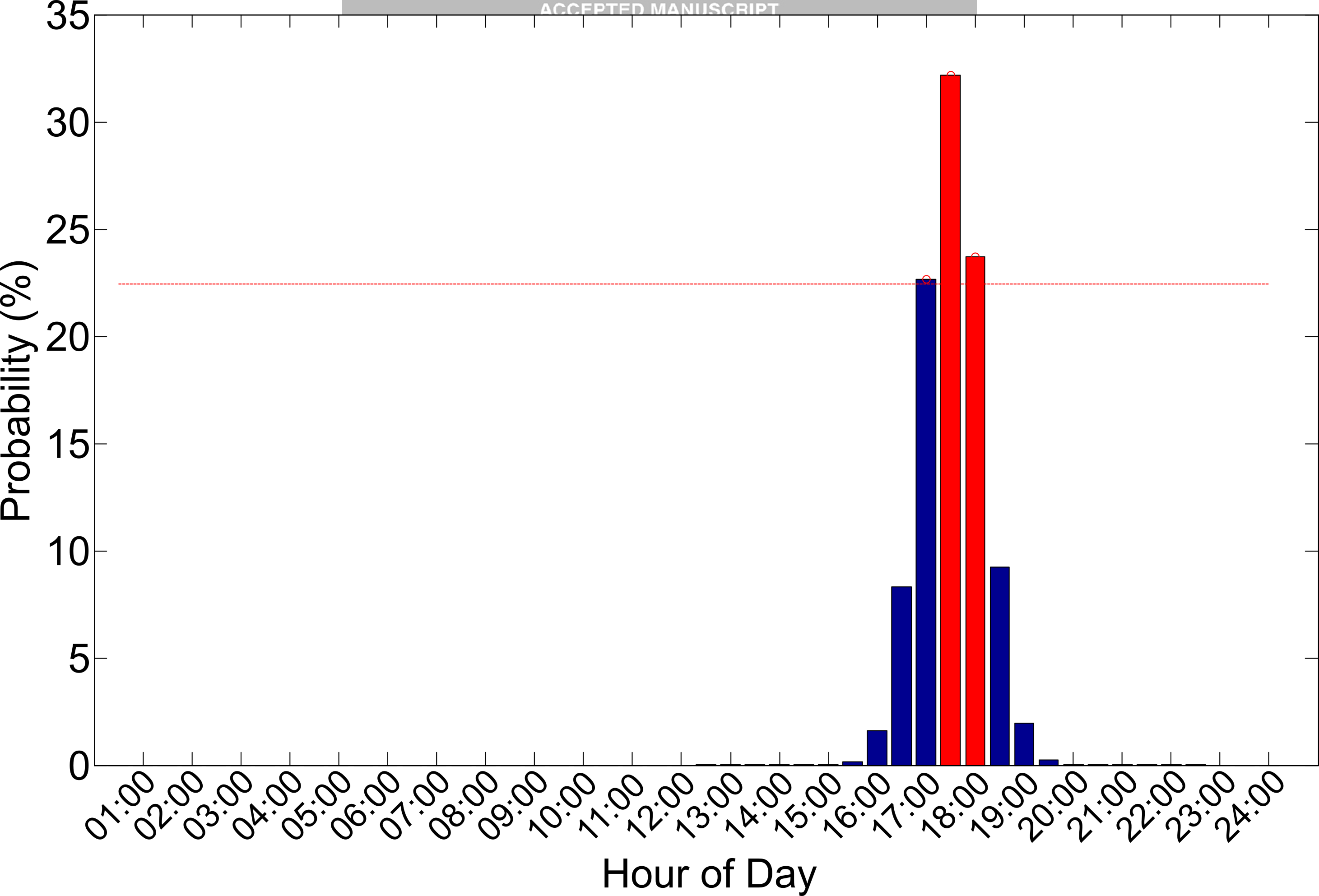

Power Demand Forecast (kW)
450
400
350
300
250
200
150
100
50
0
75.097
85.663
20.433
18.107
187.045
17.443
403.788
Building 1
Building 2
Building 3
Building 4
Building 5
Building 6
Aggregated (all buildings)

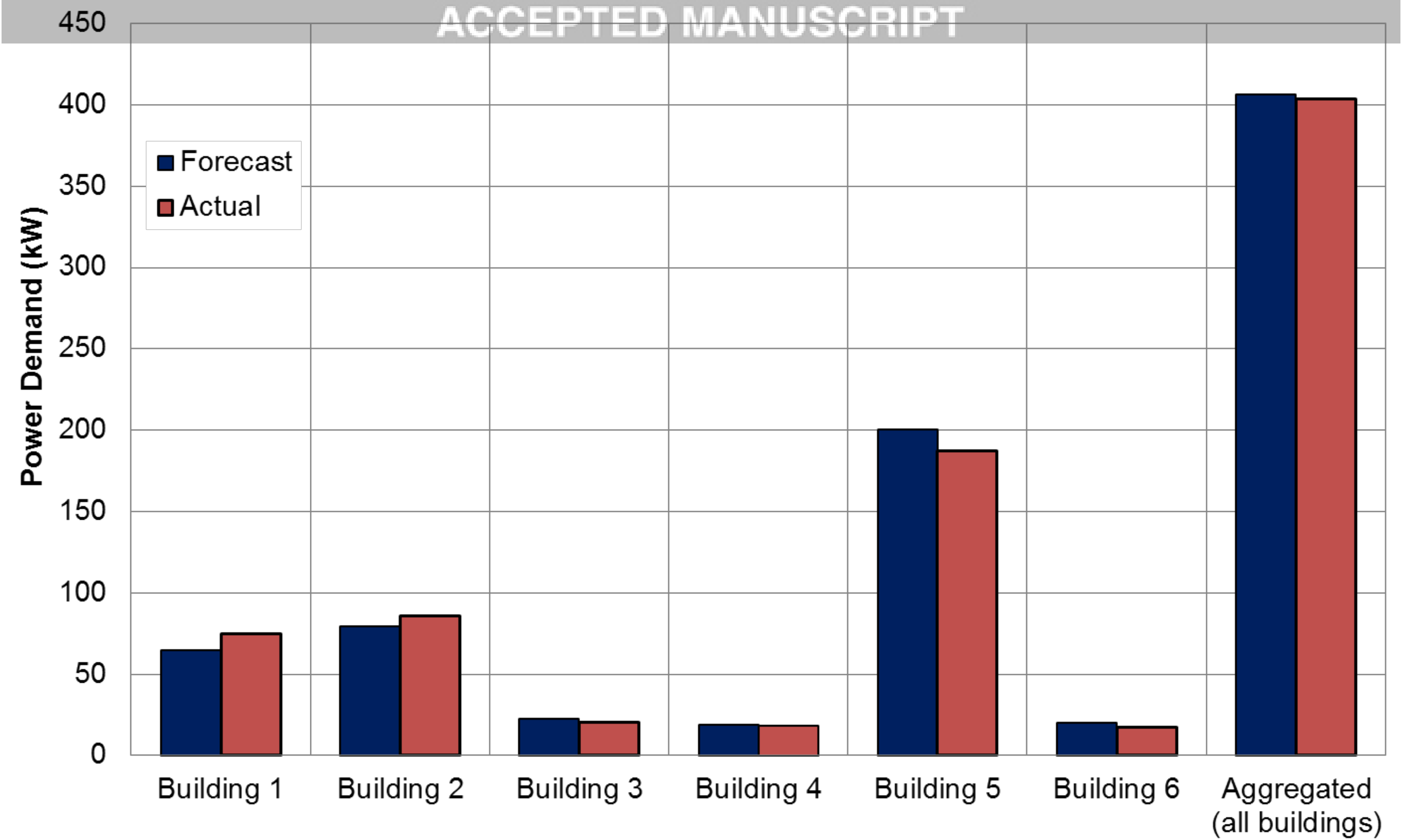


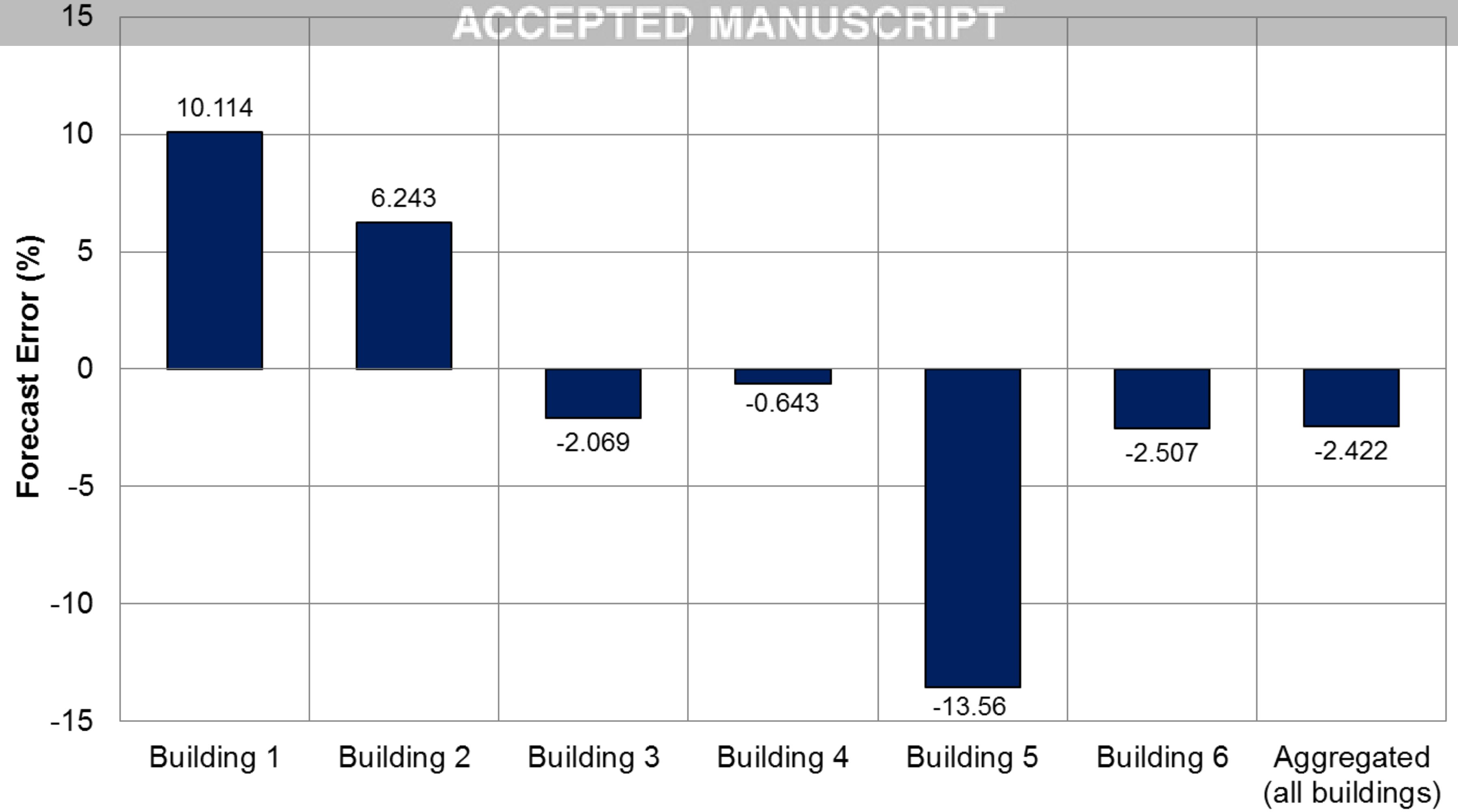
3.5
3
2.5
2
1.5
1
0.5
0
Probability (%)
0
30
60
90
120
November
December
January
February
Interval Number



Probability (%)
0
2
4
6
8
10
0
6
12
18
24
November
December
January
February
Interval Number


Probability (%)
0
5
10
15
20
25
30
35
01:00
02:00
03:00
04:00
05:00
06:00
07:00
08:00
09:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
17:00
18:00
19:00
20:00
21:00
22:00
23:00
24:00
Hour of Day


450
400
350
300
250
200
150
100
50
0
Power Demand (kW)
Forecast
Actual
Building 1
Building 2
Building 3
Building 4
Building 5
Building 6
Aggregated (all buildings)


15
10
5
0
-5
-10
-15
Forecast Error (%)
10.114
6.243
-2.069
-0.643
-13.56
-2.507
-2.422
Building 1
Building 2
Building 3
Building 4
Building 5
Building 6
Aggregated (all buildings)