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AN ARTIFICIAL NEURAL NETWORK IN SHORT-TERM ELECTRICAL LOAD FORECASTING OF A UNIVERSITY CAMPUS: A CASE STUDY

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ABSTRACT

This paper presents an artificial neural network (ANN) for forecasting the short-term electrical load of a university campus using real historical data from Colorado State University. A spatio-temporal ANN model with multiple weather variables as well as time identifiers, such as day of week and time of day, are used as inputs to the network presented. The choice of the number of hidden neurons in the network is made using statistical information and taking into account the point of diminishing returns. The performance of this ANN is quantified using three error metrics: the mean average percent error (MAPE); the error in the ability to predict the occurrence of the daily peak hour; and the difference in electrical energy consumption between the predicted and the actual values in a 24-hour period. These error measures provide a good indication of the constraints and applicability of these predictions. In the presence of some enabling technologies such as energy storage, rescheduling of non-critical loads, and availability of time of use (ToU) pricing, the possible DSM options that could stem from an accurate prediction of energy consumption of a campus include the identification of anomalous events as well the management of usage.

NOMENCLATURE

AMI	Advanced metering infrastructure
ANN	Artificial neural network
DSM	Demand-side management
LM	Levenberg-Marquardt
MAPE	Mean average percent error
MLP	Multilayer perceptron
NARx	Nonlinear autoregressive with exogenous input
STLF	Short-term load forecasting
ToU	Time of use

INTRODUCTION

Electrical distribution designers and operators have extensively used electrical load forecasting for resource planning and generation dispatch [1–3]. These predictions are often based on inputs such as weather variables, time of day, and type of day. With the advent of Smart Grid technologies such as an advanced metering infrastructure (AMI), information regarding electrical power consumption is often available in real-time and the techniques of load forecasting developed for utilities are proving useful in predicting electrical load on a consumer scale [4–6]. The alteration of electrical energy consumption based on this information, termed demand-side management (DSM), offers opportunities for the consumer to increase efficiency or decrease costs of their electrical power usage. Utilities could also apply this information to make decisions about capacity deferrals and peak shaving.

Predicting the load on a system helps operators minimize the costs associated with operations and generation efficiency,

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as well as increases the reliability of meeting demand. While forecasting has been largely focused on a utility scale, the opportunity to use these techniques is being explored on a consumer or end-user level, through DSM. DSM is a term originally coined as "systematic utility and government activities designed to change the amount and/or timing of the customer's use of electricity," although, this study encompasses the possible activities of consumers in DSM [7]. The objective of a DSM program is to reduce the price of electricity based on decreased capital costs to the utilities, as well as introduce more control to the active consumer, via information. This is a significant aspect of the desired characteristics of the *Smart Grid* outlined by the 110th Congress [8].

The concept of DSM represents a shift in paradigm of end-user energy consumption. Changing the levels and timing of electricity demand at the customer end is an alternative to utilities investing in more capital infrastructure, as well as an opportunity for consumers to engage in active participation of energy trade with utilities [9]. Added advantages include increasing energy efficiency, lowering emissions, and prolonging availability of traditional energy supplies [10]. The advent of Smart Grid technologies engages the customer with the utility to participate in decisions related to electricity consumption. This could potentially lead to a more automated decision-making process for facilities and building energy managers at the end-user level. A basis for this knowledge is an AMI that provides the participants information about electricity use. This is being done at many places around the country [11–13], and the world [14], [15], including Colorado State University- the location of the case study presented in this paper- where power quality meters for single buildings are accessible over a secure internet site.

Another strong influence on DSM is the changing rate structures of retail electricity. Deregulated markets are emerging all over the world, incentivized by the theory that competitive markets lead to the lowest possible rates. Most of these deregulated markets end up as only a skeleton of a fully competitive environment to protect the consumers at the secondary distribution levels from the high fluctuations in electricity prices, although some utilities have offered this option to the secondary distribution level (residential) customers [16]. A popular alternative is time of use (ToU) pricing. In the ToU structure, the price is based on historical and forecasted demand for a blocked time of the day. Prices are then set for a period of the day, with the intent to incentivize lowered electricity consumption during the forecast peak usage time of the system. Many utilities and regions are heading in this direction [17–19].

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

STLF has become one of the major areas of research in electric power engineering because it is essential to the efficient operation of a power system. Many prediction techniques have been used, including statistical, expert system, and artificial intelligence [3]. The system load is influenced by a number of factors, including: economics, time, weather, and random effects [20]. One of the challenges associated with STLF is that these factors influence different areas in different ways and therefore require some specificity built into the prediction algorithms [21].

Artificial neural networks (ANNs) have received an extensive share of the research attention in STLF since the late 1980's. Hippert et al. explore the growth of ANNs in electrical load forecasting with particular focus on the variation with which the success is measured. The lack of any accepted standards for ANN reporting has led to skepticism within the power systems community, even though the ANNs often perform as well as, if not better than, the more standard models. The two main shortcomings in the associated literature has been a problem of over-fitting of the data and the lack of systematic testing of the network [22], [23].

The typical structure of ANNs in this area of research has 24 output nodes representing the hourly loads of the day. Each of these hours has multiple inputs, which often includes historical data as well as weather and time variables. A number of statistical techniques as well as artificial intelligence have been combined with ANNs for pre and post-processing. The pre-processing of data is best analyzed by considering the most correlated variables, with the calendar date being considered the most influential [22]. Separating the weekends from the weekdays is a popular method in pre-processing if the types of days are noticeably different in the region [24]. Weather variables are the second most important factor affecting load profile. Reference [25] presents an in-depth look at which variables most affected the load profile, based on case studies on a realistic system, i.e., the Egyptian Unified System, by calculating linear correlation coefficients. Significant findings of [25] include the identification of historical load as the most influencing factor, while temperature as the most influential weather variable, especially in summer and fall.

Another challenge in neural network design is the decision on the complexity of the hidden layers [23], [26]. Extensive research has addressed this issue with a number of conclusions, but little agreement on a standardized method [22], [26]. The number of hidden layers, as well as the number of neurons in the hidden layers, affects the complexity of the network, and in turn, the ability of the ANN to give an accurate forecast with out-of-sample data [22], [23]. In this paper, a trial-and-error technique that looks at a different numbers of neurons is employed for this purpose. The technique presented in the paper also uses *early stopping*- a technique that employs a part of the data to test how well the network is generalizing. This is

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known as cross-validation, and is a widely used technique that may achieve good generalization even if the neural network is designed with too many parameters [22], [27].

The study presented in this paper focuses on the ability of an artificial neural network to predict the 24-hour load profile of a university campus by utilizing a number of weather variables, time identifiers, and historical data. A number of error measures that could be useful to decision-makers in a DSM application are also presented.

METHODOLOGY

Campus information and data

Prior to describing the ANN, it is pertinent to present some descriptive details of the Colorado State University main campus. Colorado State University is located in Fort Collins, Colorado (N40 34.39686 W105 5.274 [28]) and has about 200 buildings spread over an area of roughly one square mile which is used to varying degrees by a population of approximately 30,000 enrolled students and 3850 faculty and staff members on the campus [29]. The average electrical load over the period considered in the case study is around eleven MW. The monthly climatic data for Fort Collins, CO is given in figure 1.

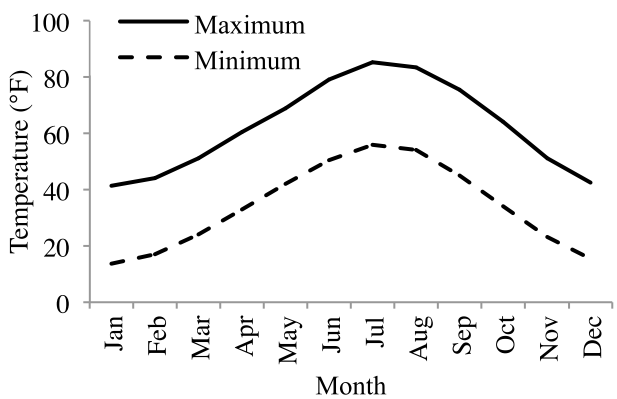

Figure 1. Monthly climatic data for Fort Collins, CO [30].

The electrical load profiles of the Colorado State University main campus are forecast with an ANN that has weather variables and non-parametric identifiers as inputs. The electrical power data logged at the main campus of the Colorado State University, located in Fort Collins, is hourly, and spans the time period from June 2006 to June 2011, with weather variables collected for the same time period and at the same data granularity [31]. The network is tested on the last 121 available days in the dataset (all days in 2011 for which data was available for this case study). Daily forecasts are produced for the 24-hour period starting at 1 A.M. The start and end times are arbitrary and could be changed in an energy management system to reflect the most efficient time of day to train the network without loss of forecast accuracy. The ANN is structured for data nearer in time to the prediction date to be more influential to the forecast. This time-series technique allows for growth and changes in consumption patterns over the five-year period to be accounted for by the network.

Artificial neural network

ANN's perform computations to mimic the learning processes of the human brain. ANN's consist of a parallel-distributed structure of neurons that uses the *learned knowledge* to match inputs to outputs and make the "map" of the inputs to outputs available for use [27]. In the case of load forecasting, the inputs provided to the neurons of the network are: weather variables, historical power consumption data, and time identifiers, and the output response is the magnitude of the active power consumption in any given hour (kW). The kW value used in training is actually an average value of power over the previous hour, and the predicted outputs are handled in a similar manner.

ANNs are especially useful in modeling non-linear relationships in part due to the non-linear structure of the neuron interconnections. Given the vastness of the literature on ANNs, the authors desist from providing a more detailed introduction to ANNs in this paper and point to the following classical references [27], [32] for a brief introduction to ANNs.

Pre-processing of Data

Processing of data is performed prior to training to improve the forecasts as well as focus the predictions on the days where load profile manipulation is most effective in offsetting costs and improving efficiency. Colorado State University has a distinct weekday profile that is different from the weekend, as illustrated in figure 2. This paper considers weekdays, termed 'occupied days', to be more important than weekends in load profile management; hence, the efforts are focused on forecasting the hourly electrical energy consumption for the 'occupied days'. University holidays have a similar profile to the weekends, and are therefore part of an excluded set. Training the networks with only occupied days improves the performance of the prediction, although the distinction of occupied days is a subjective consideration given the nature of a campus that has varying degrees of activity. Standard semester breaks are considered 'unoccupied,' excepting winter break, which is observed to have enough activity over most of it to be included in the dataset for training and prediction. There were also a number of days where data was missing, and these have been excluded from the dataset. Another exclusion from training was an outlier created by a power outage event in Fort Collins. The reason for excluding the power outage event is justified by a four-nines (N_9=3.9) reliability of electricity supply available to the campus [33].

Once the data has been processed to include only the occupied days, the dataset is divided into a training set and a validation set. The network described in this paper uses 75% of the data for training and the remaining 25% for validation. The purpose of a validation set is to avoid over-fitting of the data, which will decrease the generalization capabilities of the network causing poor predictions. A subset of the data is used

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for evaluating the performance of the model. The validation set stops the training, commonly referred to as *early-stopping,* if over-fitting occurs.

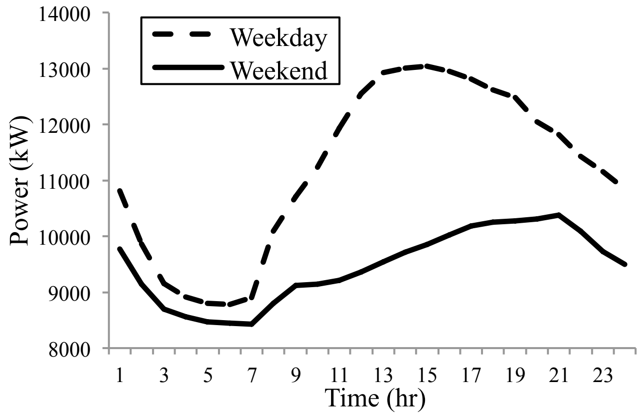

Figure 2. Typical weekday and weekend load profiles.

Another step in pre-processing is the normalization of the data before being used for the training phase. Here, the minimum and maximum values of each category are normalized to [-1 1]. This is standard practice before applying the inputs to the network, as shown in [34], so that particular inputs are not overly influential because of the scale on which they are measured. An example of a day of exogenous inputs to the network is shown in table 1. The actual weather data logged at [31] for the corresponding day was used in the network for modeling weather-related variables, although in practice these variables could be based on forecasts. Reference [35] looks at how weather forecasting accuracy can affect the quality of the electrical load prediction, which is a possible avenue for continued research for this specific application. There is also a feedback loop that uses data from the previous 24-hour period as an input.

Network Structure

The ANN for STLF for the main campus of Colorado State University is a time-series forecaster that utilizes the sequence of inputs as informative to the prediction. Figure 3 shows the basic structure of the network. This is representative of a non-linear autoregressive with external inputs (NARx) ANN, which is a dynamically-driven recurrent network that consists of an input layer, a hidden layer, and an output layer. The choice of one hidden layer is a combination of historical success [22], and the desire to maintain the simplicity of the architecture, in accordance with Occam's razor, with acceptable predictions. The output power at time *t* is informed by inputs presented to the network with no delay, at time *t*, as well as with a one-hour delay, at time (*t*-1). The power from the previous 24-hours is the recurrent component of the network. The power output is fed back through to the input layer with a 24-hour delay associated with it, i.e., hours 1-24 of the previous day informs the output of hour 1 of the current day, and so on. The autoregressive aspect of the network acts to provide the last forecasted power value to the input side for the next step in the prediction. Figure 3 is simplified in that the delayed inputs are not shown.

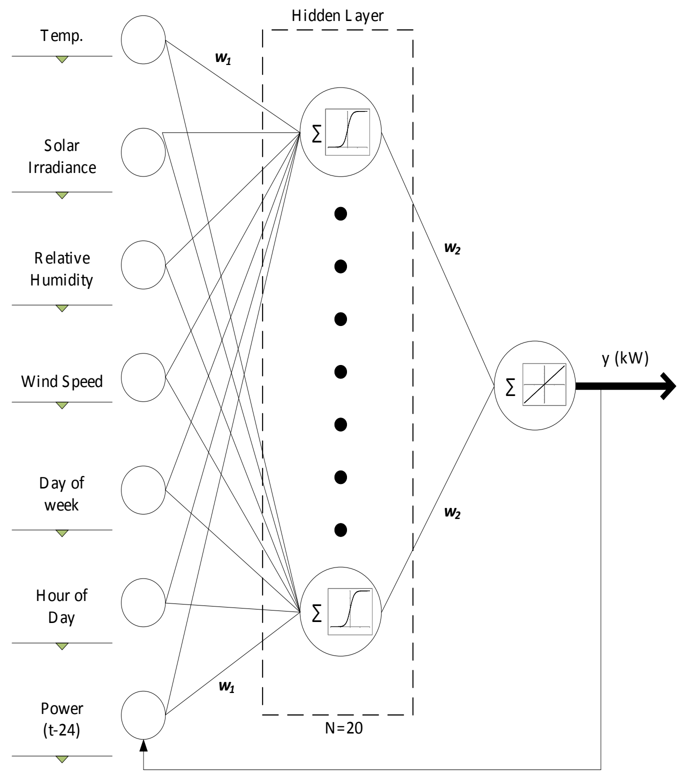

Figure 3. Architecture of the ANN.

A recurrent network is a feed-forward, multilayer perceptron (MLP) network that attempts to build the autocorrelation structure of a series internally, essentially building a memory of how things are changing, which is used in the forecasting map [32]. This is especially important in the case presented in this paper because of the large period of time that the experimental dataset spans. The five-year period that is used for training involves many new building and energy-use renovations as well as new structures on campus. MLP networks are flexible, which makes them a good choice when there is high complexity within the data [32]. The hidden layer contains nonlinear neurons that perform continuous, nonlinear transformations of the weighted inputs [32]. The activation function employed here is the sigmoid logistic function, defined as,

$$y = \frac{1}{1 + e^{-u}} \tag{1}$$

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

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Table 1. Example of exogenous inputs to ANN.

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

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

Training consists of adjusting weights on the input layer and the output layer until the combination of weights and inputs creates an acceptable output. This is achieved by the Levenberg-Marquardt (LM) learning method, which is one of the most popular optimization methods and is often the most efficient at converging to the optimum weights [32]. It is a second-order method that combines the advantages of both the Gauss-Newton and steepest descent methods to minimize the error. The error measure used by LM is the mean squared error.

The number of neurons in the hidden layer is an important aspect in designing the architecture of the ANN. There are many rules of thumb for choosing the number of neurons in the hidden layer, although there is no standardized method. It is often a subjective choice, which is exemplified in the extensive review of [22]. The approach presented here combines a measure of error on multiple test sets, as well as some subjectivity in the final decision. Observations of the prediction accuracy of the network with one to fifty neurons, on a single day as a test set, was used to determine the number of hidden neurons. Each network size was run thirteen times in hopes of achieving a good average, but was also constrained by computation time. The number of hidden neurons was decided based on the variance of the predictions and the diminishing returns in the mean average percent error (MAPE) when another neuron was added.

Performance Measures

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

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$$MAPE = \frac{\sum\left(\frac{|\vec{F}-\vec{T}|}{\vec{T}} * 100\right)}{n} \qquad (2)$$

where $\vec{F}$ is a (1xn) set of forecast values, $\vec{T}$ is a (1xn) set of observed values, and n is the number of points being forecast, which in this case is 24. Three additional performance measures that are informative when looking at the forecasting accuracy are: 1) the ability to predict the hour of the peak; 2) the maximum error throughout a twenty-four period; and, 3) the difference in total electric energy consumed over the twenty-four hour period, indicated by the area contained by the load profile curve (figure 2, load v. time). The maximum error is the ratio of the largest residual to the target value ((T_{max}) occurring at that hour.

$$Max\ error = \frac{|\vec{F}-\vec{T}|_\infty}{T_{max}} * 100. \qquad (3)$$

The energy difference is the ratio of the difference in electric energy consumption corresponding to the forecast and the observed values to the electric energy consumed corresponding to the observed values, for a 24-hour period.

$$Energy\ difference = \frac{\int_0^{n-1}\vec{F} - \int_0^{n-1}\vec{T}}{\int_0^{n-1}\vec{T}} * 100 \qquad (4)$$

Forecast Load Profile

The forecast load profile is given as an average of a set of three load profiles output by the ANN for a given data input set. This is done in an attempt to minimize the random effects of the initialization of the weights. The test sets are 24-hour periods that are out-of-sample sets of data, meaning that the network has never been exposed to the day that is predicted. The training and validation sets are comprised of all the data available previous to the forecast day. In this case study, data corresponding to 121 separate forecast days, all of which are in 2011, are presented.

RESULTS

The results of the hidden layer size test are shown in figures 4a and 4b. Each boxplot represents thirteen separate predictions on the same test day. The variability comes from the initialization of weights and biases. There is a decrease in the error as more neurons are added, although judgment is exercised to decide on the diminishing return obtained from the addition of an extra neuron. It is observed in figure 4 that there is a relatively small variance, no outliers, and low error around twenty neurons; hence, this is incorporated in the ANN architecture. A summary of three of the error measures is shown in table 2.

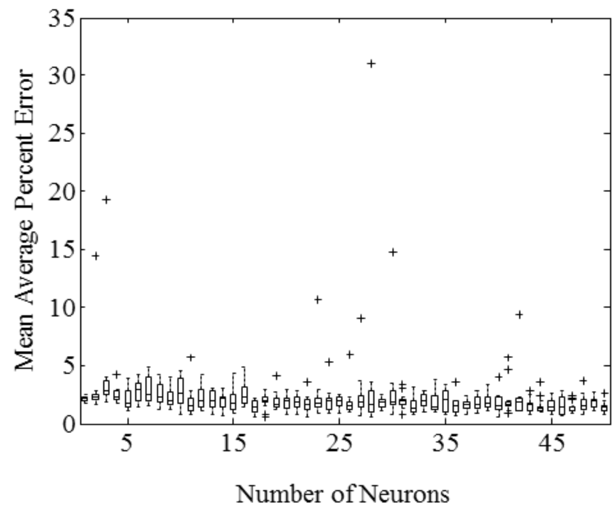

Figure 4a. MAPE versus number of neurons in the hidden layer of the ANN.

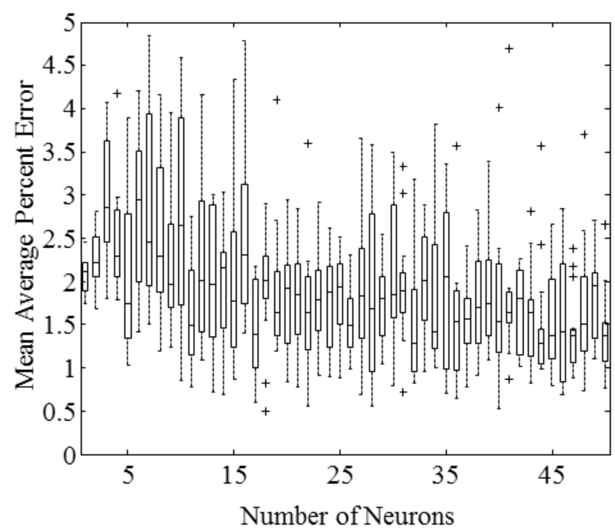

Figure 4b. A zoom-in of 0-5% MAPE versus number of neurons in the hidden layer of the ANN.

Table 2. Summary of error measures from 121 forecasts.

Average Error	Value
MAPE (%)	2.48
Maximum error (%)	5.67
Energy difference (%)	1.00

The average of the three predicted values corresponding to each day is considered as the 'forecast' for that day, and the errors shown in table 2 represent the average of all 121 'forecasts.' It is noted that according to [3], errors in the range of 2-3% are considered normal for a prediction period of 24-

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hours. Since this corresponds to a utility scale, the errors corresponding to the ANN presented in this paper, as shown in table 2, are acceptable.

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

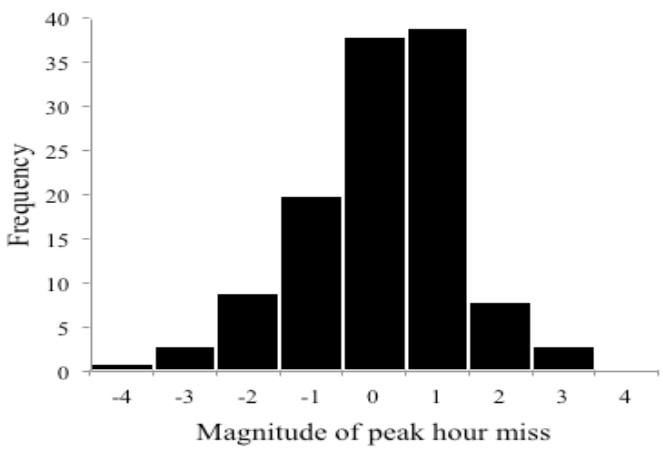

Figure 5. Error in peak hour prediction of the 121 test days.

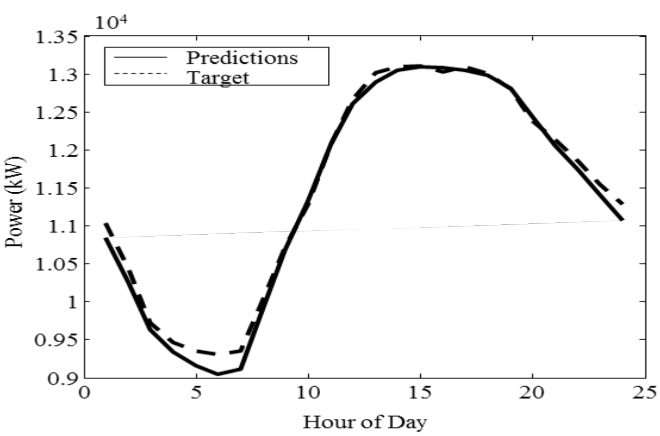

Figure 6. Typical load profile and forecast for 24-hour period.

The difference in electrical energy consumption over a twenty-four hour period between the predicted and actual values is smaller than the MAPE not only because it looks at a different measure, but because the energy difference is averaged over negative and positive residuals. The MAPE is penalized for misses, both high and low, because it uses the absolute value of the residual. An example of a predicted load profile forecast and the actual values is shown in figure 6. The MAPE on the sample day is 1.51%, which is below the average value shown in table 2. Figure 7 provides an indication on the performance of the ANN from the standpoint of the MAPE. It is observed that the distribution is skewed to the left, although there are some days that provided relatively poor predictions.

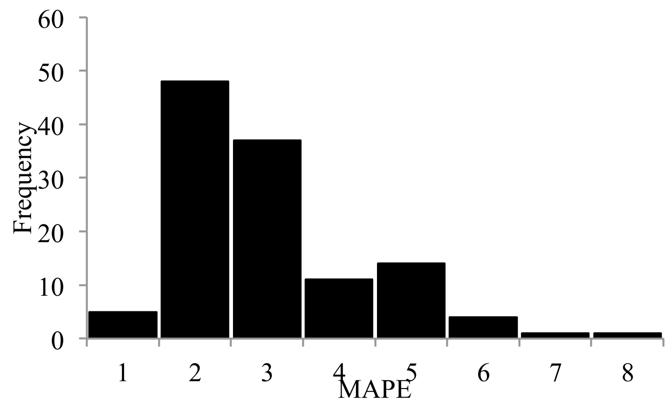

Figure 7. MAPE over 121 test days.

DISCUSSION

The different error measures provide useful insight into how the forecast can be used for a varying approach to DSM. The ANN, in its present form, may be used for gaining predictive knowledge on the electrical load forecast of the university campus; which may then be used in achieving a DSM goal such as decreased overall daily electrical energy consumption. If it is advantageous for an active consumer to reduce peak demand based on some rate structure, or other motivation, it is vital to understand the limitations of the ANN's ability to accurately predict the hour at which peak occurs. Improving on this aspect of the forecast is an avenue for further research, although realizing the limitations of the forecast could result in a successful localized application to peak shaving as well.

The distribution of the MAPE provides an indicator to performance of the network - approximately 25% of the time the MAPE is over 3%. Future exploration into the context of these days (input data) may provide an explanation on the inability of the ANN to produce a better result. The authors acknowledge the existence of a simple explanation, although the relationship of the outputs to the day of the week was explored which yielded no clear correlation to poor predictions.

The error in the daily electrical energy consumption suggests that this ANN could be useful in quantifying an energy

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savings goal. There are a number of applicable situations on a university campus that may provide an avenue for reconciliation between the comfort of the campus occupants and the opportunity for energy savings. This could also be used in contract negotiations for energy saving measures with the local electric utility.

The ANN forecasts may also be utilized by building energy managers as a medium to detect anomalous events. It may allow for the detection of faulty hardware before the performance of that hardware is noticeable on a utility bill, potentially saving days of inefficient operation of a building.

Comparing this forecasting technique to a 'simpler' prediction algorithm such as multiple linear regression technique is currently underway, although data is not available for comparison at this time. The authors believe that it provides predictions that are accurate enough to make a DSM program feasible for a university campus type end-user.

Further research involves applying this type of forecasting to smaller scales such as feeders and buildings within the end-user campus, in an effort to make the DSM more manageable for decision makers. The decision making process that follows a forecast is also an area under investigation, and is the prime reason for exploring forecasting at this scale.

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