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Energy Forecasting for Event Venues: Big Data and Prediction Accuracy

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***Abstract*— Advances in sensor technologies and the proliferation of smart meters have resulted in an explosion of energy-related data sets. These Big Data have created opportunities for development of new energy services and a promise of better energy management and conservation. Sensor-based energy forecasting has been researched in the context of office buildings, schools, and residential buildings. This paper investigates sensor-based forecasting in the context of event-organizing venues, which present an especially difficult scenario due to large variations in consumption caused by the hosted events. Moreover, the significance of the data set size, specifically the impact of temporal granularity, on energy prediction accuracy is explored. Two machine-learning approaches, neural networks (NN) and support vector regression (SVR), were considered together with three data granularities: daily, hourly, and 15 minutes. The approach has been applied to a large entertainment venue located in Ontario, Canada. Daily data intervals resulted in higher consumption prediction accuracy than hourly or 15-min readings, which can be explained by the inability of the hourly and 15-min models to capture random variations. With daily data, the NN model achieved better accuracy than the SVR; however, with hourly and 15-min data, there was no definitive dominance of one approach over another. Accuracy of daily peak demand prediction was significantly higher than accuracy of consumption prediction.**

Keywords: energy prediction, energy forecasting, smart meters, Big Data, sensor-based forecasting, machine learning.

1. Introduction

Recent advances in sensor technology and the proliferation of smart metering devices that measure, collect, and communicate energy consumption information have created possibilities for development of sophisticated energy services. Big Data collected by smart energy meters have created opportunities to analyze energy use, identify potential savings, customize heating and cooling activities for savings and comfort, measure energy efficiency investments, provide energy cost estimates for real estate buyers, and educate about responsible energy usage and conservation.

This potential has been recognized by governments and industries, which resulted in the Green Button initiative [1]. This initiative is an effort to provide utility consumers with easy and secure access to their energy usage data and the ability to share these data with third parties. Smart meter data are provided to consumers in a standardized Green Button format which facilitates data sharing, integration, and reuse. With the Green Button format, consumers can permit the access of their energy use data to take advantage of the growing range of energy applications, products, and services to help them conserve energy and manage their electricity bills. Presently, over 43 million households and businesses have access to their energy usage data in the Green Button format [2], which creates tremendous possibilities with respect to energy management. London Hydro, the local electrical utility involved with this project, has developed the first cloud based Green Button Connect-My-Data test environment to allow for data access to academic partners with the customer's consent.

A typical premise in data analytics, and especially in Big Data analytics, is that more data have the potential to lead to new insights and better business decisions. This is especially true with machine learning algorithms that can learn better with more data. However, massive data sets pose challenges due to their size and complexity [3, 4]. With sensor technologies, we can collect large data sets, but these sets might be difficult to process. This study considers different sensor reading intervals, investigates how more data impact energy forecasting accuracy, and looks into trade-offs between accuracy and processing time.

Moreover, this work explores the opportunity to use Green Button data to predict electrical energy consumption for large commercial customers, specifically event venues including sports arenas, concert halls, theatres, and conference centers. Such consumers are especially interested in energy forecasting on the event level (a specific concert, game, etc.) because this affects pricing for use of the facility.

Event venues can be expensive facilities to operate; the cost of electricity for sports arena can exceed $3,000 per day [5]. Ice rinks, by their nature, are large electricity consumers with standard arenas using around 1.5 GWh/year [6]. Thus, there have been significant efforts in improving efficiency in ice arenas: several projects provide recommendations on best practices and reduction measures to help reduce their operating costs [6]. Consequently, it is important to address this type of buildings in an energy prediction study. Moreover, forecasting energy consumption in the presence of different events, will assist venue operators to estimate energy cost of future events and it will enable them to include energy cost in the facility usage fee.

This study was oriented to support energy management operations and decision making by Spectra Venue Management at Budweiser Gardens in London, Ontario. This

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study estimates future energy consumption by considering past energy consumption available through Green Button and contextual information about future events such as event type and schedule. Although the focus is on event-organizing venues, the proposed approach can be used by any consumer that is impacted by some form of operating schedule, such as hotels, conference centers, and schools. Unlike typical sensor-based approaches which rely on energy readings and meteorological information [7, 8], this work takes advantage of contextual information in the form of an event schedule and attributes.

It is important to highlight the difference between energy consumption and demand: *consumption* is the total amount of energy used, expressed in KWh, whereas *demand* is the immediate rate of that consumption, often expressed in KW. Commercial consumers are typically charged for both consumption and demand, although the pricing models differ among distribution companies [9]. Consequently, in addition to consumption prediction, commercial consumers are interested in predicting energy demand peaks because lowering these peaks would result in a reduced electricity bill. Therefore, this paper considers consumption and peak demand prediction.

The type of consumer, the event-organizing venue, makes prediction especially challenging. Energy consumption in office buildings [10] usually resembles a very distinctive pattern similar to that shown in Figure 1, with lower consumption overnight and on weekends. In contrast, the consumption variations of an event-organizing venue, as shown in Figure 2, are much larger and do not exhibit a strict pattern similar to those of office buildings. Consumption increases during an event, and the actual pattern and magnitude are related to the event attributes such as type (hockey, basketball, …) and seating configuration.

Because of the challenges described, it is expected that prediction accuracy will not be as high as for residential buildings or offices; however, it is important to address this category of consumers.

The rest of this paper is organized as follows: Section 2 reviews related work, and Section 3 introduces neural networks, support vector regression, and performance metrics. The methodology, including the data set, the prediction models studied, and model building, is described in Section 4. An evaluation is presented in Section 5, and Section 6 concludes the paper.

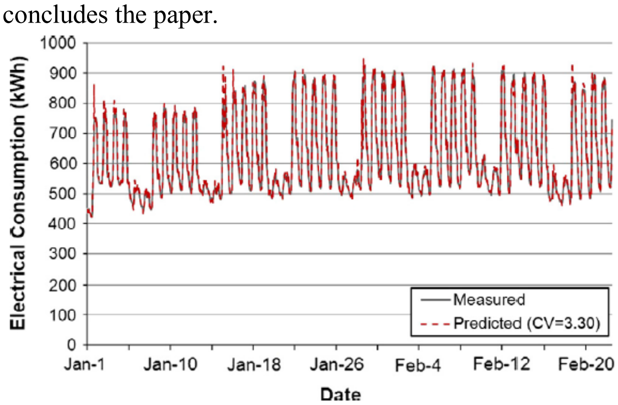


Figure 1: Building energy consumption [11]

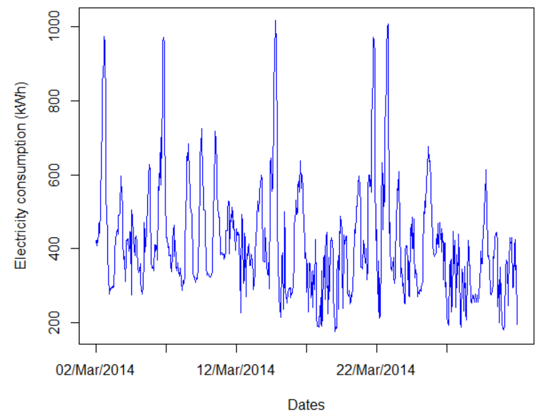


Figure 2: Event venue energy consumption

2. Related Work

A large number of research studies have addressed various aspects of electrical energy prediction such as a nation's annual electricity consumption [12], the annual energy consumption of an industry sector [13], the annual energy consumption of the residential sector [14], and daily or hourly energy demand using smart metering technology [11, 15].

Annual electrical energy consumption has been found to be related to population growth, economic growth, energy prices, energy intensity, and other factors [16]. Estimating annual energy consumption on a national or regional level is important for planning electrical production capacity; however, annual consumption does not account for demand peaks, and the generation capacity needs to be able to provide for these peak demands. Moreover, annual energy consumption prediction has very limited relevance to energy conservation efforts. Wholesale market prices for electricity are driven by a supply-demand relation, which further increases the need to predict demand variations.

The interest in demand prediction together with the proliferation of smart metering has resulted in a shift in forecasting efforts to daily and hourly consumption prediction [11, 15]. This paper explores daily, hourly, and 15-min interval prediction for consumption and peak demand and compares their accuracy.

The work of Jain *et al.* [11], like this paper, explored the impact of temporal granularity (daily, hourly, 10-min intervals) on the accuracy of electricity consumption forecasting. They achieved the best results with hourly intervals and monitoring by floor level. However, whereas Jain *et al.* studied a residential building, this research is concerned with large commercial customers, specifically event-organizing venues. To handle large variations in energy consumption caused by events, we include contextual information about future events such as event type and schedule. Moreover, in addition to consumption prediction, our work also includes peak demand prediction.

To plan for demand peaks and to bill event organizers adequately for use of the venue, it is important to predict peak demand. Fan *et al.* [17] developed a prediction model for next-day building energy consumption and peak power demand. Similarly, short-term forecasting has been considered in a number of other studies [18–20]. However, in the case of event organizing, the prediction timeframe is much longer, six month to one year or even two years, as the estimated energy cost needs to be included in early venue booking negotiations. Moreover, although the energy consumption of office and hotel buildings as explored by Fan *et al.* [17] exhibits weekday/weekend/holiday patterns, the energy use of an event venue is driven by event type and schedule. Quilumba *et al.* [8] recognized the importance of differences in energy consumption patterns and proposed a prediction approach which groups customers according to their consumption behavior. Our work explores the possibility of adapting approaches from residential and/or commercial settings to predict electricity consumption and demand for event-organizing venues. Energy prediction is especially important for venue owners because they need to account for energy when they provide quotes for use of the venue.

Various techniques have been used to predict electrical energy needs, including neural networks (NN) [21], support vector machines (SVM) [11], autoregressive integrated moving average (ARIMA) models [17], clustering models [22], decomposition models, gray prediction [10], and regression models [23]. Suganthi and Samuel [16] reviewed models for energy demand forecasting and observed that the focus had shifted from residential to commercial and industrial domains. They noted that neural networks have been used extensively for electricity forecasting and considered them suitable for industrial energy prediction. Support vector regression (SVR) was considered as an emerging technique, together with genetic algorithms and fuzzy logic.

Ahmad *et al.* observed that NN and SVR are widely used in electrical energy forecasting, and therefore their review [24] focused on the use of NN and SVR for building energy prediction. They concluded that the two models each have their own advantages and disadvantages and that it is inconclusive which one is the best for energy forecasting.

Tso and Yau [25] compared the performance of three energy prediction models: regression analysis, decision trees, and NNs. In the winter phase, NNs performed slightly better, whereas in the summer phase, the decision tree model performed somewhat better than the other two. As in the work of Ahmad *et al*. [24], it was inconclusive which model was best overall.

Kialashaki and Reisel [14] evaluated regression models and neural networks with respect to predicting the annual energy consumption of the residential sector in the United States. In terms of accuracy, the models studied were not significantly different; however, the authors observed that due to their sensitivity to economic crises, NNs are likely more realistic.

Because a number of studies have highlighted the significance of NNs and SVRs in electricity demand and consumption prediction, this work explores the use of NNs and SVRs in the context of Green Button and of event-organizing venues.

While energy consumption in office buildings exhibits repetitive, and a quite stable pattern, consumption of an event-organizing venue varies greatly and does not follow time-based pattern; this makes energy prediction for such consumers difficult. Sensor-based approaches typically use historical energy readings and meteorological information [7, 8]; in addition to those attributes, our approach also incorporates event contextual information such as event type and schedule. Several mentioned studies consider short-time forecasting [18–20]; in contrast, long-time forecasting is needed for event venues. Moreover, we also explore the impact of data granularity to evaluate when it is important to use shorter interval readings.

3. Background

This section introduces the two machine learning approaches used in this study, neural networks and support vector regression, and describes the performance metrics used to compare the prediction models.

3.1. Neural Networks

Neural networks (NN) [26] are a family of machine learning models inspired by the human brain and used to approximate functions that are generally unknown. Like a human brain, neural networks consist of interconnected neurons. There are many types of neural networks such as radial basis function networks, Kohonen self-organizing networks, and recurrent networks; however, here the focus is on feed forward neural networks (FFNNs) because the FFNN is one of the most frequently used NNs for energy forecasting [27] and, as such, is used in this study as well.

Figure 3 shows a three-layer FFNN that can be used to approximate non-linear functions without assuming relationships between inputs and outputs. The information in the FFNN moves in one direction, from the input layer through the hidden layer(s) to the output. In such a network, there are no connections between neurons in the same layer. The number of neurons in the input layer corresponds to the number of input features, and the number of neurons in the output layer is equal to the number of outputs. An FFNN can have more than one hidden layer, but often a single layer is sufficient. The number of hidden layers and the number of neurons in each hidden layer are chosen by the user.

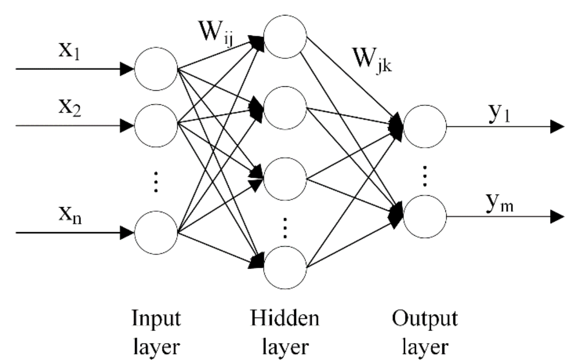


Figure 3: Feed forward neural network

The output of each neuron in the hidden layer is determined as follows:

$$y_j = \varphi\left(\sum_{i=1}^{N} w_{ij}x_i + w_{io}\right),$$

where the x_i are neuron inputs, the w_{ij} are synaptic weights connecting the i-th neuron in the input layer to the j-th neuron in the hidden layer, and w_{io} is a bias which shifts the decision boundary, but does not depend on any inputs. φ is an activation function which is usually modelled as a step or sigmoid function. The output of the neurons in the output layer is modelled in the same way, with the weights corresponding to connections between the hidden and output layers.

FFNN weights are learned during the training phase, using backpropagation in conjunction with an optimization method such as gradient descent. To start the learning process, the weights are randomly initialized. Next, the input is applied and the output calculated according to the feedforward process described earlier. The calculated output is compared to the known output, and the calculated error is propagated backwards through the network. During this backpropagation, the weights are adjusted according to the optimization method to reduce the error for that specific input. The process is repeated for all training examples, and the overall process is repeated until the error drops below a pre-defined threshold.

3.2. Support Vector Regression

Support vector machines (SVM) [26][28] are supervised learning models used for classification and regression problems; a version of SVM for regression is referred to as support vector regression (SVR). SVR is characterized by a high degree of generalization, which indicates the model's ability to perform accurately on new, previously unseen data. In SVR, support vectors are training samples which lie on the ε-tube bounding decision surface, as illustrated in Figure 4. Observations within the ε-tube do not influence predictions; in other words, residuals less than ε do not get penalized.

Suppose that an output Y is modelled as a function of input variables X, given a training data set $\{(X_i, Y_i)\}_{i=1}^{i=N}$. The SVR approximates the relationship between input and output as:

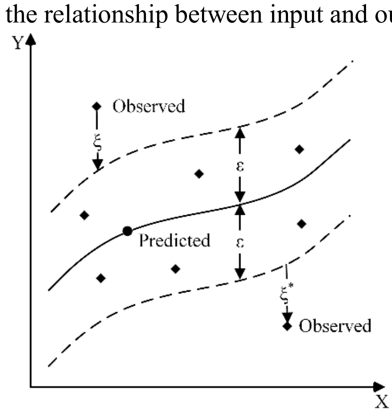


Figure 4: Nonlinear SVR, adapted from [8]

$$Y = W \cdot \Phi(X) + b,$$

where $\Phi(X)$ is a nonlinear kernel function which non-linearly maps from the input space X to the feature space. Coefficients W and b are determined by minimizing the following function:

$$Minimize\ \frac{1}{2}\|w\|^2 + C\frac{1}{N}\sum_{i=1}^{N} \xi_i + \xi_i^*$$

subject to constraints:

$$Y_i - W \cdot \Phi(X_i) - b \leq \varepsilon + \xi_i$$

$$W \cdot \Phi(X_i) + b - Y_i \leq \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \geq 0$$

where W is a weight vector which needs to be as flat as possible to achieve good generalization. Terms ξ_i and ξ_i^* capture residuals beyond the ε boundary (Figure 4), and cost C is the regularization parameter that determines the penalty for errors greater than ε.

The radial basis function (RBF) is a widely used kernel for mapping the input space to a high-dimensional feature space. The RBF is also efficient to compute and has only one parameter that needs to be determined; hence, this work also uses the radial basis kernel. The RBF kernel is expressed as:

$$K(x, x') = \exp(-\gamma\|x - x'\|^2),$$

where parameter γ specifies the influence of each data point.

3.3. Performance metrics

To assess model accuracy, this work uses two metrics: the mean absolute percentage of error (MAPE) and the coefficient of variance (CV).

The MAPE metric has been used in a number of electricity prediction studies [17] [29]. It expresses average absolute error as a percentage and is calculated as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i} \times 100,$$

where y_i is the actual consumption, $\hat{y}_i$ is the predicted consumption, and N is the number of observations.

Like MAPE, the CV metric has often been used in energy prediction studies [8,26]. It evaluates how much error varies with respect to the actual consumption mean and is calculated as follows:

$$CV = \frac{\sqrt{\frac{1}{N-1}\sum_{i-1}^{N}(y_i - \hat{y}_i)^2}}{\bar{y}} \times 100,$$

where y_i, $\hat{y}_i$, and N represents the same elements as in MAPE and $\bar{y}$ is the average actual consumption.

Additionally, the difference in cumulative daily consumption between the different models and methodologies is evaluated. The same MAPE and CV metrics are used, with the exception of y_i and $\hat{y}_i$, which represent the cumulative actual consumption and the cumulative predicted consumption for the i-th day, and N, representing the number of days.

With respect to demand prediction, the focus here is on the accuracy of the predicted daily demand peaks because these peaks drive overall electricity cost. In other words, the main interest is not in evaluating overall demand prediction accuracy, but in the accuracy of demand peaks. Accuracy is still evaluated using the same MAPE and CV formulas, with the exception of y_i, which represents the actual peak demand for the i-th day, $\hat{y}_i$, which is the predicted peak demand for the i-th day, and N, representing the number of days.

4. Methodology

This work uses two machine learning approaches for electricity forecasting: a neural network and support vector regression. For each machine learning approach, several model variants are investigated, and their accuracy is evaluated.

Because the choice of prediction model and its input variables depends on the actual prediction scenario, this section first introduces the data set with the corresponding prediction scenario. Next, the studied prediction models are described. Each prediction model is generic so that it can be used with both NN and SVR. Finally, this section describes how the prediction models are built, optimized, and tested.

4.1. Data set

Because this study is concerned with energy prediction for event-organizing venues, the data set includes energy consumption and demand readings for an event venue. Figure 5 shows hourly consumption readings over the two-year period acquired through the Green Button program. There is no easily visually notable seasonal pattern; however, drops in consumption can be noted in Jun and August which coincides with the venue maintenance schedule.

Throughout the year, there are large consumption spikes coinciding with occurrence of various events. This highlights the importance of including event schedule data and event attributes in prediction. Thus, the data set consists of two parts: the first part contains energy data obtained from smart meters and the second part includes event-related attributes.

To analyze consumption patterns further, Figure 6 displays energy consumption over a few days, with vertical bars indicating event duration. Note that an increase in energy consumption on the day of an event starts in the morning, coinciding with the start of set-up activities for that event. Electricity consumption drops sharply upon event completion. During non-event days, consumption generally increases during the day and drops overnight; however, there are additional variations throughout the day. To capture high

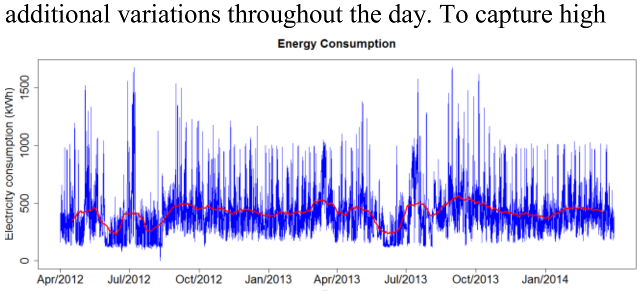


Figure 5: Energy consumption over two years

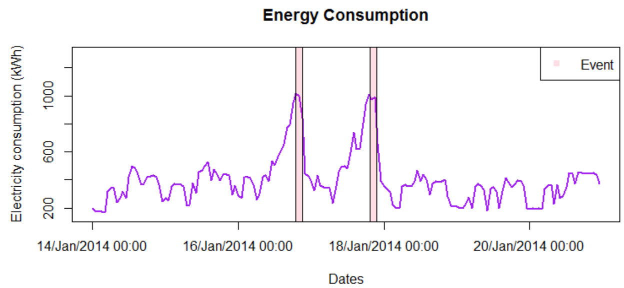


Figure 6: Energy consumption and events

energy consumption during events, the prediction model will rely on event date and time, and to account for the increase on the morning of the event, the hour of the day and the event day indicator will be used as input variables.

4.2. Prediction Models

All prediction models are designed to work with both NN and SVR. Each model will be evaluated with NN and SVR as well as with different data granularities. Because this work aims to develop an approach to be integrated into a commercial product, special attention is paid to ease of use. This especially pertains to event data; an effort is made to keep the required event data limited and simple to collect to reduce the barrier to entry.

For each model, and for each data granularity, one observation is associated with one energy reading. Other features, including event-related attributes, were added to the energy reading data set.

Model 1 (M1): *The base model* defines the set of core input features that impact the energy consumption and demand of an event-organizing venue; it is a base for accuracy comparisons. Specifically, the base model includes the following input variables:

- *Event Type*: basketball, hockey, and other. From the event history, it is possible to distinguish basketball and hockey, but classifying other events would require extensive manual annotation, and therefore they are placed in the "other" category. Because there is no specific order of categories with respect to energy consumption, each one is treated as a separate model input with possible values of 0 and 1. The event schedule is also indicated in this way: it is 1 for energy readings during which an event is occurring and 0 for all other readings.
- *Day of the year*: 1 to 365. Outside temperature is often a factor in energy prediction models [24], but in the case of event organizing, due to long prediction timelines of up to a year or even two, accurate temperature prediction is limited. Therefore, to account for temperature changes and seasons, this model uses day of the year as an input. This prevents weather forecasting errors from affecting energy prediction error.
- *Event day*: 0 or 1. As previously mentioned, on event days, energy consumption increases early in the day due to event set-up. This parameter, together with *hour of the day*, will help the model to predict this increase.

- *Hour of the day*: 1 to 24. This input will account for day/night consumption variations and with addressing the energy increase due to preparations for an event.
- *Seating configuration*. This accounts for different venue configuration with different seating capacities.

In an attempt to improve the accuracy of the prediction model, the following additional models were explored:

- **Model 2 (M2):** *The base model with hours before an event*. Set-up for events typically occurs a number of hours before the event and results in an increase in energy demand; the demand continues to increase until the peak value, which typically occurs during the event. To try to capture this increase due to set-up activities more effectively, the *hours before event* variable has been added as a model input.
- **Model 3 (M3):** *One step ahead*. A number of energy prediction models use the known electrical consumption values from the previous time step *(t-1)* to predict consumption at time step *t* [11, 29]. This approach is iterative because to predict consumption at time t_n, consumption needs to be predicted for t_0 to t_{n-1}, where t_0 is the last known consumption. The drawback of this approach is that the addition of a single future event requires recalculating consumption values for the complete prediction timeline.
- **Model 4 (M4)***: Two separate models* for event and non-event days. Energy use patterns are very different for event and non-event days; overall daily consumption is much higher on event days, and peak demand on an event day can be several times higher than on a non-event day. Hence, in this approach, two separate models are created, one for event days, and one for non-event days.

To observe the impact of data granularity, the prediction models described above were evaluated with daily, hourly, and 15-min data. In the case of daily and hourly data granularity, the Green Button 15-min data were aggregated as follows:

- Daily/hourly energy consumption is the sum of 15-min energy consumptions:

  $$EC = \sum_{i=1}^{n} EC_i,$$

  where EC_i is the energy consumption for the *i*-th interval, and *n* is the number of intervals.
- Daily/hourly energy demand is the highest demand reading for the observed day/hour:

  $$ED = \max_i(ED_i) \ where \ i = 1, \dots 24 \ ,$$

  where ED_i is the energy demand for the *i*-th 15-min interval.

Results obtained with daily, hourly, and 15-min data were compared to evaluate the significance of data granularity. The time period considered was always the same, independent of data granularity. Therefore, the ratio of daily, hourly, and 15-min data set size is 1:24:96. Working with a 96 times larger data set (15-min in comparison to daily) is much more time-consuming and resource-intensive; hence, the results obtained should justify the use of bigger data sets.

In Big Data research, having more data is associated with higher accuracy and increased business value. This work explores the impact of data granularity on the accuracy of electricity prediction models in the context of an event-organizing venue. Model 2, the base model with hours before an event, was not considered with daily data because the samples represent daily values and there is no concept of "hours before an event".

4.3. Model building

Model building here refers to choosing the model configuration suitable for the prediction problem at hand and training the chosen configuration. Each technique, NN and SVR, has parameters that need to be determined during the learning phase. For NNs, a single hidden layer is typically sufficient, but the number of hidden neurons and the learning rate need to be chosen according to the prediction problem. For SVR with a radial basis kernel, two parameters need to be determined: the cost C, which determines the penalty for errors greater than ε (Figure 4), and the γ parameter of the radial basis function.

Each combination of model parameters constitutes a *model configuration*. For each technique, NN and SVR, for each model described in Section 4.2, and for each data granularity, the best model configuration needs to be chosen. Estimating the performance of different model configurations to choose the best one is referred to as *model selection*. Once the best model is selected, *model assessment* estimates its prediction error on new data.

The model selection process is described in Figure 7. The process is the same for NN and for SVR, as well as for all models described in Section 4.2 and all data granularities. First, the data set is divided into a training set and a testing set. The *testing set* is a portion at the end of the data set reserved solely for model assessment; this set is not used for model building or model selection. The remainder of the data, the *training set*, are used for model selection and for supervised learning.

Model selection was carried out applying blocked cross-validation, a variant of *k*-fold cross validation, on the training set, as suggested by Bergmeir and Benítez [30]. In *k*-fold cross-validation, a data set is randomly partitioned into *k* subsets of equal size. One subset is reserved for validation, and the remaining subsets are used for training. The process is repeated *k* times (*k*-fold), each time using a different subset for validation. The results from *k* repetitions are averaged to form a final error estimate. Blocked cross-validation is different from *k*-fold cross-validation in the way that the data are partitioned: instead of random data points, each subset consists of continuous data points from the time series.

As illustrated in Figure 7, step 3, a set of configurations C is formed by assembling a grid of parameters. In the case of SVR, these configurations consist of various combinations of *C* and γ parameters, whereas with NN, the number of hidden neurons and the learning rate are varied. The training set is

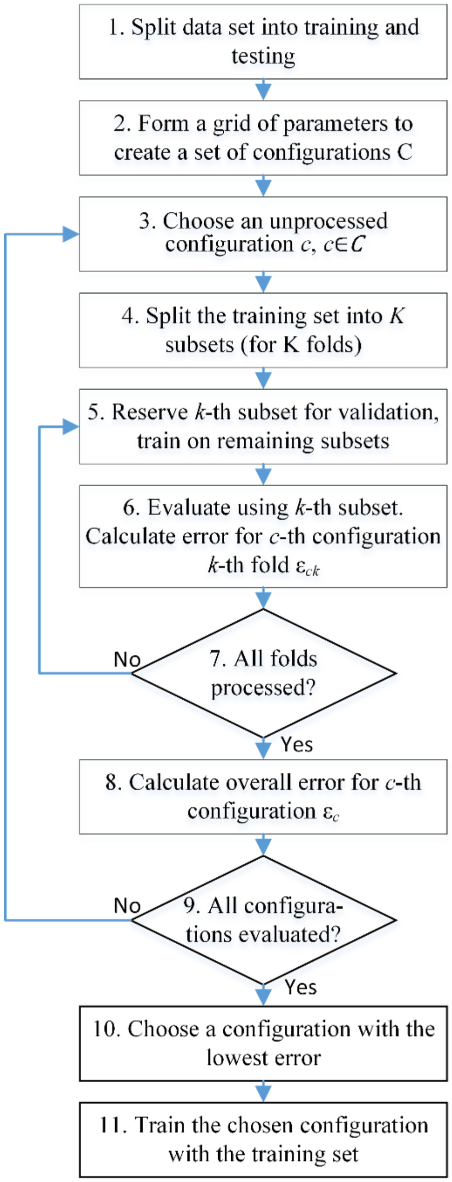


Figure 7: Model selection process

split into K subsets (step 4), where the number of splits equals the number of folds in k-fold cross-validation. Steps 5 to 7 represent the folds of the cross-validation, and step 8 estimates the overall error for the c-th configuration.

The process proceeds from step 9 by processing the next configuration. After all configurations have been processed, the configuration with the lowest error ε_c is selected (step 10), and the model is trained using the complete training set (step 11). This model is then evaluated on the previously unseen data from the testing set.

Figure 8 illustrates parameter optimization for SVR. The cost C was varied from 1e-5 to 10,000, and γ was varied from 1e-7 to 100. For each parameter, ten values were considered; hence, the total number of configurations evaluated was 100. Colours indicate different error values.

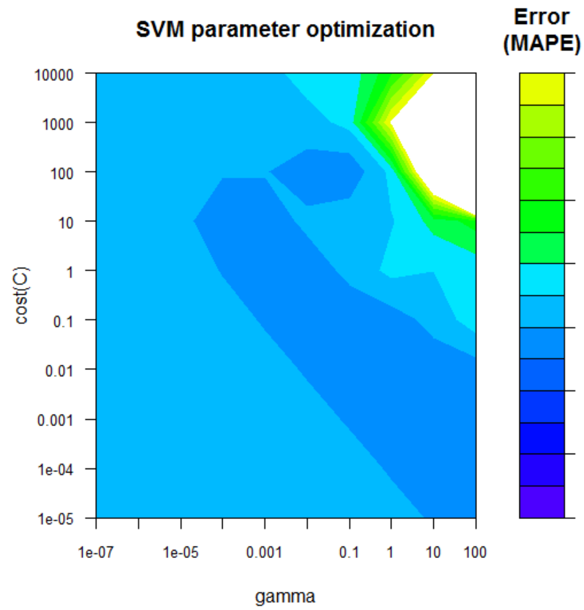


Figure 8: SVR parameter optimization

5. Evaluation

This section describes empirical data sets and implementation, presents experiments and results, and discusses findings and limitations.

5.1. Empirical data sets and implementation

The proposed approach has been evaluated on data from Budweiser Gardens, a large event-organizing venue with a capacity of over 10,000, located in Ontario, Canada. The venue is the home arena for a basketball and a hockey team. In addition, it hosts a variety of other sport events, concerts, and entertainment shows, ranging from small intimate shows to very large productions.

Energy data were obtained through the Green Button standard interface. London Hydro, the local electrical utility involved with this project, has developed the first cloud based Green Button Connect My Data test environment to allow for data access to academic partners with the customer's consent. The data consisted of 15-minute electricity consumption and demand readings from revenue grade smart meters. The data set spans from January 1, 2013 to March 31, 2014, for a total of 43,680 data points. Each data point includes the reading date, time, consumption, and demand. Hourly and daily data sets were created by aggregating the 15-min data. The hourly and daily consumptions are sums of 15-min consumption readings, and demand was calculated as the maximum of 15-min demand. 80% of the data were used for model selection and training, and the remaining 20% were used for testing. The training data set contained readings for the full 2013 calendar year so as to account for all seasons.

Because energy consumption in event-organizing venues is driven by the events hosted in the venue, event-related data have been added to the energy readings. Section 4.2 described the four prediction models evaluated, with their input variables.

The prediction models were implemented in the R language [31]. Specifically, the FFNN models were implemented using the "RSNNS" package and the SVR models using the "e1071" package.

Experiments were carried out on a small cluster consisting of two nodes, each with 24 Intel Xeon CPUs and 96 GB memory. To take advantage of the large number of processors, the code was parallelized so that different model configurations and different cross-validation folds could run in parallel on different nodes. Communication between the two nodes was established using a message passing interface (MPI).

5.2. Experiments and results

As already mentioned, two machine learning approaches, NN and SVR, and four different prediction models were considered. The process described in Section 4.3 and Figure 7 was carried out for each combination of prediction model and machine learning approach. Moreover, a similar process was repeated for daily, hourly, and 15-min data. This means that a total of 22 models were evaluated for consumption prediction and the same number of models for peak demand forecasting. For each experiment, two error measures were calculated: MAPE and CV.

Figure 9 illustrates the actual energy consumption and the predicted values obtained by NN and SVR for one month from the testing data set. In this example, the base model with hourly data was used. Vertical lines indicate the occurrence of different events. Note that the prediction models can estimate the rise in electricity consumption just before an event and the peak during the event. However, for non-event days, the prediction model does not closely follow actual consumption. This occurs because during those days, there are random hourly variations that are not captured in the prediction model. For the period observed in Figure 9, for non-event days, the predictions produced by the NN were higher than those generated by the SVR

Table 1 shows the consumption prediction errors for each of the four models: the two machine learning approaches, and the three data granularity levels. Model 2 was not considered with daily data because the "hours before event" concept does not apply with daily readings. Cumulative daily consumption errors are also evaluated; the results are presented in Table 2. Here, the consumption values, actual and predicted, are first aggregated for each day and then MAPE and CV are calculated. For daily models, MAPE and CV are the same with (Table 2) and without (Table 1) aggregation. For 15-min and hourly intervals, cumulative daily consumption errors (Table 2) are significantly lower than errors calculated without aggregation (Table 1).

Whereas Table 1 includes consumption errors, Table 3 shows peak demand errors for the same prediction models, the same machine learning approaches, and the same data granularity levels. In the context of demand-driven pricing, the accuracy of the peak demand predictions is important because these peaks drive the overall electricity cost.

Overall, the accuracy obtained was not as high as in some other studies of residential buildings or offices. For example, Jain *et al.* [11] reported CV values as low as 2.16 for a residential building using SVR with hourly data. However, Jetcheva *et al.* [32] showed that prediction model accuracy varies greatly when applied to different buildings. They also noted that commercial and industrial sites present a modelling challenge. An event-organizing venue is especially challenging due to large variations in consumption caused by events.

5.3. Discussion

To compare the accuracy of NN and SVR in predicting electricity consumption, Figure 10(a) shows MAPE and Figure 10(b) shows CV for the four prediction models and the three data granularities. It can be seen that no single machine learning approach, NN or SVR, is better with all prediction models; however, NN either outperforms SVR or is slightly inferior. It is interesting that both machine learning approaches, NN and SVR, are significantly more accurate

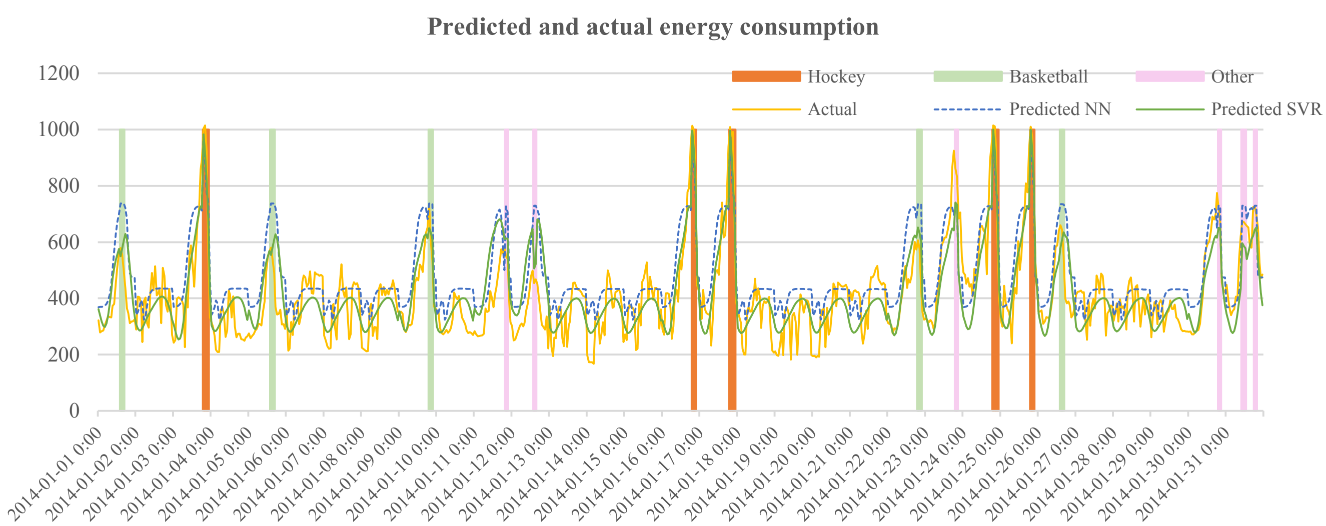


Figure 9: Predicted vs. actual energy consumption

Table 1
Consumption MAPE and CV errors for the five models and the two approaches: NN and SVR

Models	Neural networks (NN)		Support vector regression (SVR)	
	MAPE	CV	MAPE	CV
15-min intervals				
1 - Base Model	22.78	26.21	22.29	24.88
2 - Base Model + hours before event	22.88	25.87	21.58	23.84
3 - Step ahead	27.96	32.74	26.96	35.40
4 - Two models (event/non-event days)	23.27	23.41	31.63	35.31
Hourly				
1 - Base Model	20.42	23.32	19.26	22.12
2 - Base Model + hours before event	19.52	22.78	19.22	21.89
3 - Step ahead	19.87	23.60	22.74	29.67
4 - Two models (event/non-event days)	20.67	21.92	29.66	34.13
Daily				
1 - Base Model	10.25	16.72	16.44	21.30
3 - Step ahead	8.61	10.55	10.72	13.05
4 - Two models (event/non-event days)	9.37	10.84	14.06	17.52

Table 2
Cumulative daily consumption MAPE and CV errors for the five models and the two approaches: NN and SVR

Models	Neural networks (NN)		Support vector regression (SVR)	
	MAPE	CV	MAPE	CV
15-min intervals				
1 - Base Model	9.86	12.06	11.40	14.90
2 - Base Model + hours before event	12.19	16.36	11.70	15.72
3 - Step ahead	18.99	25.30	14.16	16.70
4 - Two models (event/non-event days)	10.31	12.09	13.11	15.38
Hourly				
1 - Base Model	12.05	15.22	10.48	13.32
2 - Base Model + hours before event	11.62	14.66	11.47	15.31
3 - Step ahead	12.39	16.78	12.72	15.71
4 - Two models (event/non-event days)	11.27	14.26	13.13	15.39
Daily				
1 - Base Model	10.25	16.72	16.44	21.30
3 - Step ahead	8.61	10.55	10.72	13.05
4 - Two models (event/non-event days)	9.37	10.84	14.06	17.52

Table 3
Peak demand MAPE and CV errors for the five models and the two approaches: NN and SVR

Models	Neural Networks (NN)		Support vector machine (SVR)	
	MAPE	CV	MAPE	CV
15-min intervals				
1 - Base Model	7.19	9.43	8.85	11.22
2 - Base Model + hours before event	13.32	14.89	11.52	13.8
3 - Step ahead	21.79	27.67	30.34	36.37
4 - Two models (event/non-event days)	9.28	10.70	26.82	34.82
Hourly				
1 - Base Model	10.39	11.19	7.65	10.04
2 - Base Model + hours before event	12.68	14.40	9.17	11.61
3 - Step ahead	17.30	22.90	26.17	39.80
4 - Two models (event/non-event days)	12.67	14.66	25.01	31.64
Daily				
1 - Base Model	7.64	9.36	21.81	27.20
3 - Step ahead	8.02	10.61	21.79	27.24
4 - Two models (event/non-event days)	8.51	10.52	17.21	23.18

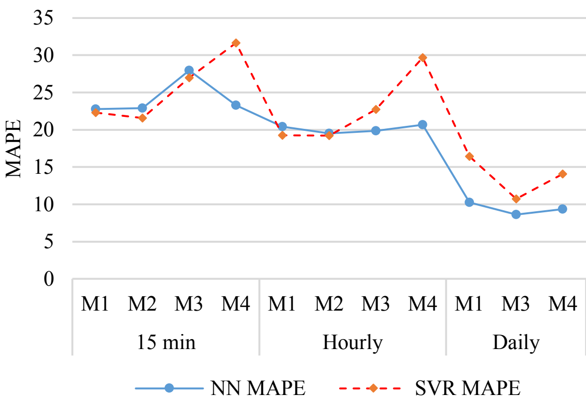
with daily data than with hourly or 15-min readings: all three models, M1, M3, and M4, show considerably better accuracy in terms of MAPE and CV errors with daily data. While MAPE and CV errors for daily data were as low as 8.61 and 10.55 respectively, MAPE errors for hourly and 15-min reading were over 19 and 21, respectively.

This can be explained by the fact that with hourly data, the model cannot capture random consumption variations, especially during non-event days, as illustrated in Figure 9. In contrast, with daily readings, the aggregation process dampens the impact of the hourly consumption variations. As shown in Figure 10, with daily data, NN accuracy is better than that achieved by SVR.

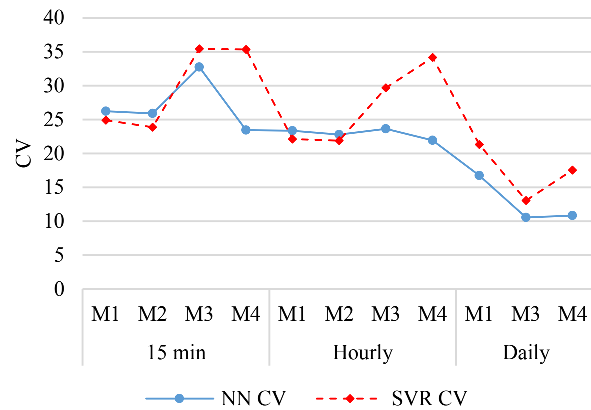
The accuracy is also evaluated on a daily level; MAPE and CV errors for cumulative daily consumption are displayed in Figure 11. While errors varied greatly when the evaluation was done on the input data granularity (Figure 10), cumulative daily consumption prediction errors were much more consistent across different granularities (Figure 11). Moreover, error rates are much lower when observed on a daily level: for hourly and 15-min readings MAPE and CV errors were under 15 and 17 respectively for most models while without aggregation all MAPE errors were over 19 and CV errors over 21. As illustrated in Figure 11 the best accuracy was obtained with NN and M3 model with MAPE error 8.61 and CV error 10.55.

While Figure 10 and Figure 11 present the consumption prediction errors, Figure 12 depicts the peak demand errors, 11(a) displays the MAPE, and 11(b) the CV. Similarly to consumption prediction, no single approach, NN or SVR, was better for all prediction models; nevertheless, NN either outperformed SVR or came relatively close. Although consumption prediction was much more accurate with daily data than with other granularities, the difference was not very large for peak demand prediction. Moreover, the overall best result, MAPE error 7.19, was achieved with NN, model M1, and 15-min data, whereas the lowest CV error 9.36 was achieved also with NN, model M1, but with daily data. Although consumption prediction with the 15-min interval data suffered from an inability to capture random variations, peak demand prediction did not have the same issue because it is concerned with predicting the highest daily peak.

In the case of NN, good results with MAPE error 8.51 or lower and CV error 10.61 or lower, were achieved with all three models, M1, M3, and M4 with daily data, but also with models M1 and M4 with 15-min data, MAPE errors 7.19 and 9.28 and CV errors 9.43 and 10.70 respectively. Because the 15-min data set contains 96 times more data than the daily data

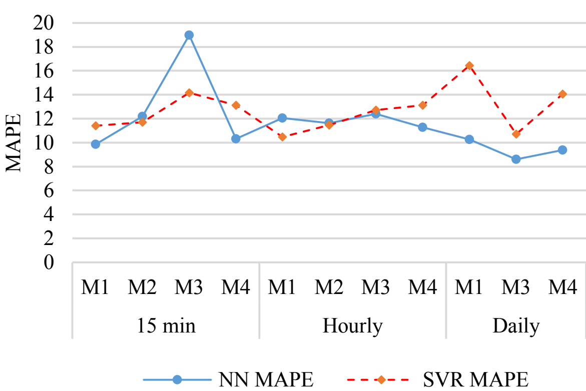


a) Consumption MAPE errors

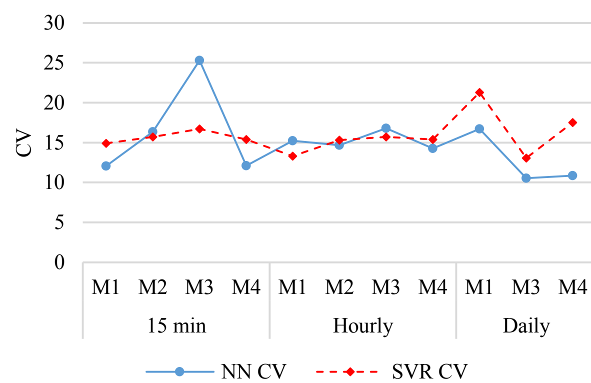


b) Consumption CV errors

Figure 10: Consumption MAPE and CV errors

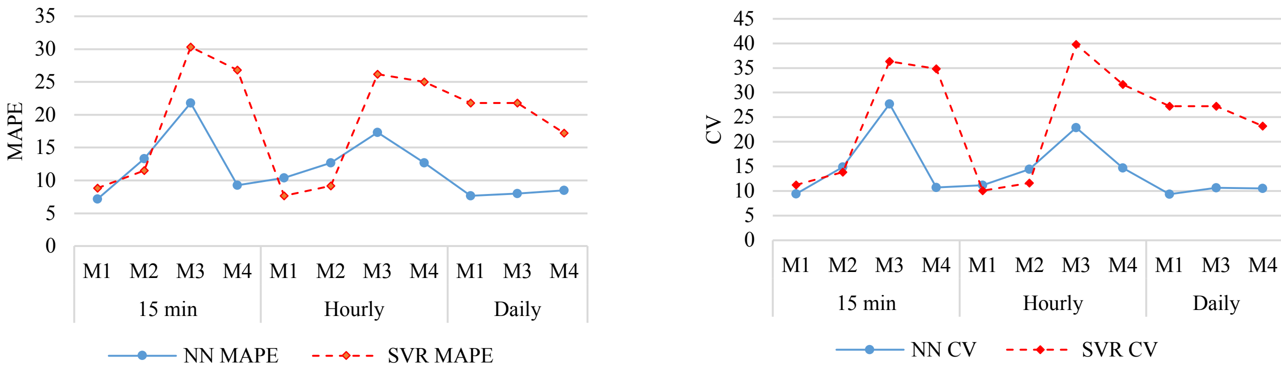


a) Cumulative daily consumption MAPE errors



b) Cumulative daily consumption CV errors

Figure 11: Cumulative daily consumption MAPE and CV errors



a) Peak demand MAPE errors

b) Peak demand CV errors

Figure 12: Peak demand MAPE and CV errors

set, the hourly data set is more suitable for peak demand prediction.

SVR errors were much higher than NN errors for daily data (Figure 12); however, the SVR achieved similar error rates, in terms of both MAPE and CV errors, to NN when the M1 model was used with 15-min data. Nevertheless, in terms of peak demand prediction, NN is considered to be a better solution than SVR because errors were much lower than with SVR with the smallest data set (daily data): MAPE error 7.74 and CV error 9.36 for NN, compared to MAPE error 17.21 and CV error 23.18 for SVR.

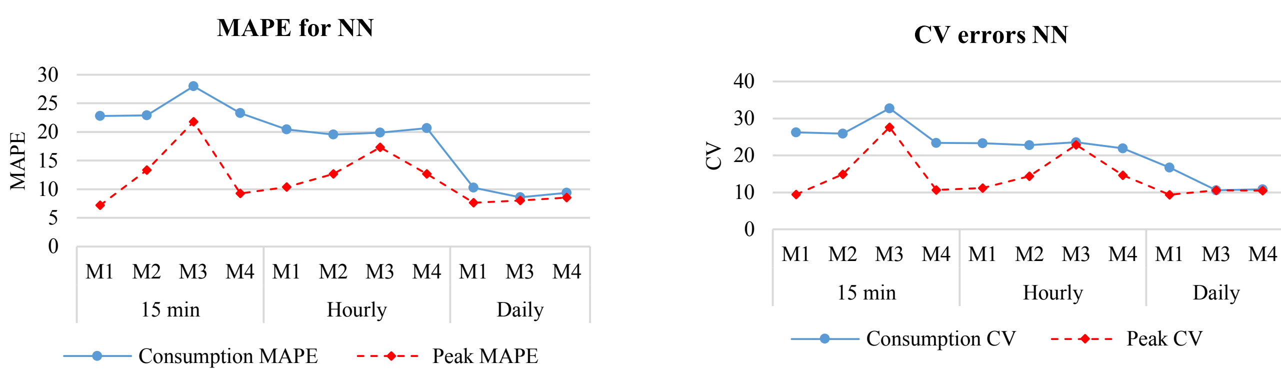
To determine which model, M1, M2, M3, or M4, and which data granularity achieved the best accuracy for each machine learning approach, Figure 13 shows the MAPE and CV errors for NN, and Figure 14 depicts the MAPE and CV errors for SVR.

Figure 13 shows that the accuracy of predicting peak demand with NN is generally higher than the accuracy of consumption prediction. Daily data resulted in overall better prediction of consumption and demand than the other data granularities. 15-min data with the M1 model showed very good accuracy in peak demand prediction, but had the disadvantage of a much larger data set.

Although NN achieved the best results with daily data (Figure 13), the situation was very different with SVR, as illustrated in Figure 14; the errors varied greatly among models and data granularities, and there was no single model that outperformed others in terms of consumption and peak demand prediction.

In terms of MAPE and CV, the best consumption prediction was obtained with model M3 and daily data, but good peak demand predictions were also obtained with models M1 and M2 with hourly data, and with model M1 with 15-min data. Due to the data set sizes, daily and hourly data sets are preferred over the 15-min data set. Therefore, SVR models M1 and M2 with hourly data are options for peak demand prediction and M3 with daily data for consumption prediction.

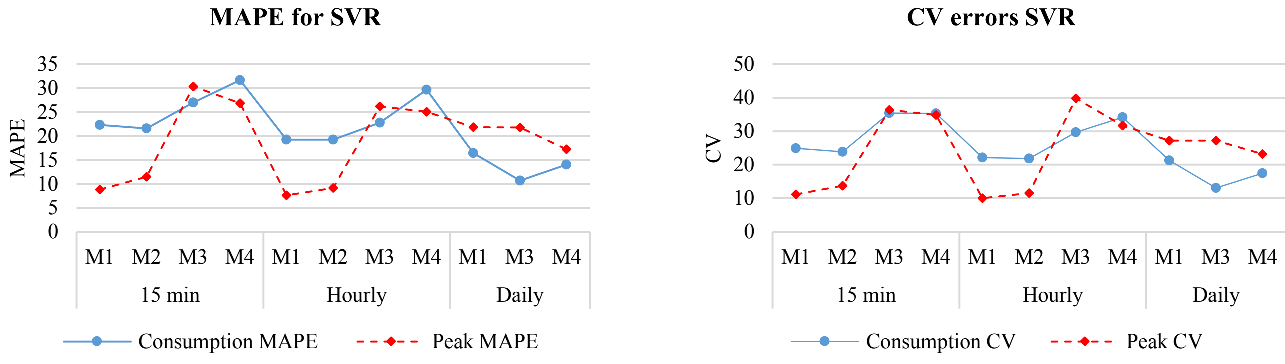
Another important aspect that needs to be considered in evaluating a prediction model is execution time. As with each data granularity, the same time periods were always considered, the ratio of data in daily, hourly, and 15-min data sets was 1:24:96. NN and SVR execution times for different data granularities and the observed models are shown in Figure 15. Because the variations in execution time are large, the results are shown on a logarithmic scale. The times shown include model selection, model training with a training data set and prediction with a test data set. For each NN and SVR, two parameters with 10 values each were considered, for a total of 100 configurations.



a) MAPE error

b) CV error

Figure 13: Consumption and peak prediction errors for neural network



a) MAPE error **b)** CV error

Figure 14: Consumption and peak prediction errors for SVR

Figure 15 shows that for hourly data, the NN models took much less time; however, with daily data, the time required was shorter for SVR. In terms of accuracy, NN outperformed SVR with daily data; hence, longer execution time is outweighed by better accuracy.

Overall, in terms of consumption prediction, daily data sets achieved better accuracy than the other data sets regardless of the machine learning approach. NN achieved considerably lower error rates, and therefore NN with the daily data set was considered the best option for consumption prediction.

In terms of peak demand prediction, specific models with 15-min or hourly data achieved slightly better accuracy than the same models with daily data. However, because model selection and training time with these data is longer and error rates only slightly lower, prediction with daily data is still a very good solution. As with consumption prediction, NN achieved better results than SVR for peak demand forecasting with daily data.

The results could be improved by adding new attributes to better describe events. We are currently in the process of discussing with Budweiser Gardens possible new attributes; examples include separating "other" category into specific event types, creating subcategories for each event type and quantifying electricity-related equipment brought into the venue by event organizers. As those attributes are not known for past events, the extensive data collection process will have to take place before they can be used for prediction.

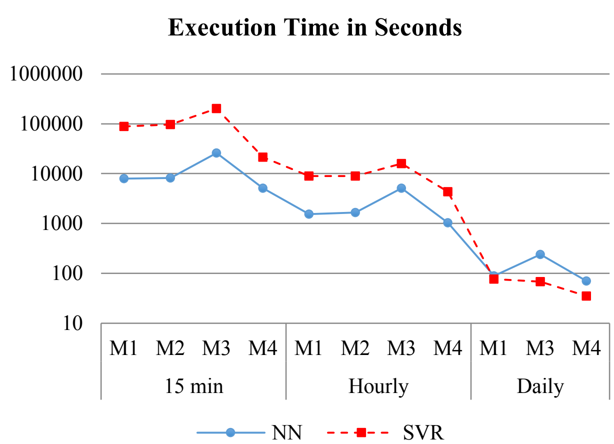


Figure 15: Execution time

6. Conclusions

Smart meters and sensors have created possibilities for collecting more detailed and finer-grained data related to energy consumption. These Big Data promise a foundation for development of new energy services and better energy management and conservation. Although a typical premise in data analytics is that the availability of more data has the potential to enable new insights and better decisions, it is important to distinguish for which applications these Big Data are truly needed.

This study explores the importance of more data, specifically the impact of temporal data granularity on the accuracy of electricity consumption and peak demand prediction. Unlike the large number of studies that have considered offices or residential buildings, this paper has studied an event-organizing venue, which is an especially difficult problem due to large consumption variations and the impact of event attributes on energy use.

Two machine learning approaches were considered, NN and SVR, and four prediction models were explored with each. In terms of consumption prediction, daily data achieved better results than 15-min or hourly data: the lowest MAPE error of 8.61 and CV error of 10.55 was achieved with NN. Cumulative daily consumption for daily and 15-min intervals has shown lower error rates than the evaluation done without aggregation; nevertheless, the accuracy with daily data was still better than the accuracy with other data granularities. With regard to peak demand prediction, the best model with daily data resulted in MAPE error of 7.64 and CV error of 9.36 which is slightly worse results compared to specific 15-min or hourly models, but the processing time was much shorter. Overall, with daily data, NNs achieved better results than SVR.

Future work will explore the applicability of the methods to other building categories. The possibility of providing energy forecasting as a service and incorporating it into business flow [33] will be investigated. Moreover, use of Big Data technologies such as Hadoop, MapReduce, and NoSQL in energy prediction will be explored.

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