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COMPARISON OF ITERATIVE-MULTISTEP-AHEAD MODELS FOR FORECASTING THE SUPPLY AIR FLOW RATE OF A HVAC SYSTEM

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Abstract: *This paper presents the development of a closed-loop autoregressive neural network (ANN) model for forecasting the supply air flow rate of a heating, ventilation and air conditioning (HVAC) system. Data was provided by the building automation system (BAS) recorded with a 15-minute time interval. The forecast horizon for the ANN model was six hours. The optimal architecture of the ANN model was found through an extensive search algorithm of over 36,750 different design alternatives. The supply air flow rate was forecasted over the testing period with a Root Mean Squared Error (RMSE) of 386 L/s and a CV(RMSE) of 1.8%. The forecasts of the ANN model are then compared with those from the support vector regression (SVR) model which had a RMSE of 463 L/s and a CV(RMSE) of 2.2%. It was concluded that both ANN and SVR forecasting methods provide acceptable forecasts of the target value. In addition, a comparison of different approaches for updating the ANN with the sliding window technique is also presented.*

Keywords: *Forecasting, ANN, SVR, HVAC, sub-hourly, air supply flow rate*

INTRODUCTION

Our cities and population are growing, as a result, so is our energy demand and emissions. In Canada, the commercial/institutional sector utilizes approximately 18% of the total electricity in Canada, CEA (2015) and NRCan (2013). Similarly, within Quebec, approximately 20% of the electricity is used for the same sectors (Quebec, 2016). Heating, ventilation and air conditioning (HVAC) equipment, lighting, and electronic appliances within these buildings have a high contribution to the demand within the electricity grid. During periods of peak demand, utilities are often faced with mismatches in power supply and demand which can stress the equipment and cause blackouts. In order to mitigate such effects, some utilities offer incentives for large energy consumers to reduce their electricity consumption during peak demand times. Demand response programs being one of the incentives offered. Concurrently, the rapid decline in microprocessor costs, increased memory capacity, rising processing speed and ease of deployment has led to many buildings deploying building automation systems (BAS) in an attempt to record and automate building operations.

In the context of demand-side management offered by some utility companies, the short-term forecasting of electricity demand in buildings plays an important role. The literature review of forecasting models revealed three main types of forecasting models: white, grey and black box models.

White box/forward/physics-based models are those based on physical laws and are typically used in the design phase of the building. For example, these models are used in sizing the HVAC equipment, comparison of design alternatives, and showing design compliance with standards. Programs such as EnergyPlus, TRNSYS, and eQuest are some examples which implement such models. Physics-based models are more useful in the design stage rather than the prediction of real energy demand. This is because many variables are needed in the calibration of a physics-based model. Thus, these models can be time-consuming and expensive to construct.

Black box/inverse/data-driven models are based solely on measurements. Their accuracy depends on the model selected, and quality and quantity of the data available. Such models are easily adaptable, can model nonlinear phenomena, and quick to deploy. However, they are normally less efficient when they are used with data far from the training conditions. Neto and Fiorelli (2008) compared the use of a physical model and a data-driven model. The ANN model had a slightly better performance than the EnergyPlus program for forecasting the daily energy consumption of a university building. When compared to the measured building data, the ANN forecasts had a 10% average error while the EnergyPlus model had 13%.

The final modeling technique discussed in this paper is a grey box or hybrid model. These models combine approaches of both physics-based and data-driven models

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in order to benefit from their respective advantages. For example, a hybrid model can incorporate physical laws and parameters which can be calibrated with available measurements. Li et al. (2009) compared the forecasted hourly cooling load of an office building by using two models, ANN and Support Vector Machine (SVM). The results from those two models had equal errors (1.2%) when compared with measured data.

De Rocco et al. (2007) compared the forecasting of the electricity grid by using the ANN and SVM models. The architecture of the ANN was found by adjusting the number of hidden layer neurons on a trial and error based approach. The SVM led to a mean absolute percentage error (MAPE) of 3.3% for the first week and 3.0% for the second. The ANN led to a MAPE of 2.5% and then 7.1% for the second week.

Kaytez et al. (2015) performed a comparison of SVR and ANN for forecasting the yearly electricity consumption of Turkey. The input of the ANN was composed of four independent variables and the architecture was found through exploring different transfer functions, learning algorithms, and the number of hidden layers. The output layer consisted of the net electricity usage for the year. It was found that the SVR model, with a RMSE of 1.44 TWh, performed slightly better than the ANN model with a RMSE of 1.82 TWh.

Among the few studies on the performance of forecasting for HVAC equipment, Le Cam, Zmeureanu, and Daoud (2013) compared the use of ANN, kernel regression, and SVR models. The application was for forecasting the electric demand of a chiller in a building. The SVR results had a CV(RMSE) of 15% on the first day which converged to approximately 20% over the complete testing set. The ANN was found to have a larger CV(RMSE) of 24.9% over the first day and reached approximately 22.4% over the week.

Chou & Bui (2014) used artificial intelligence (AI) techniques in order to provide a comparison of forecasted heating and cooling loads. Synthetic data was used from 12 buildings simulated in Ecotect program. Forecasting models included: ANN, SVR, general linear regression, classification and regression tree, chi-squared interaction detector, and an ensemble method. It was found that the ensemble method of the ANN+SVR provided the best forecasts of the buildings cooling load with a RMSE of 1.57 kW. The closest forecasting models in terms of performance were SVR with a RMSE of 1.65 kW, and the ANN which had a RMSE of 1.68 kW.

Tang, Kusiak & Wei (2014) presented the modeling and short-term energy prediction of an air handling unit (AHU). Different forecasting techniques were used as part of the model selection process. The multilayer perceptron (MLP) ensemble was chosen as it outperformed the other models by having the lowest MAPE of 3.62%; compared to MLP with 3.79%, SVM with 7.01%, and 7.63% for the random forest model.

From the literature review, we concluded that most publications dealt with forecasting for the whole building or territory; few studies presented forecasting at the subsystem/equipment level. This paper presents the development of an ANN model for forecasting the supply air flow rate of an AHU in an institutional building. The case study was a university research building in Montreal, Canada. Data was obtained from the BAS at 15-minute intervals. The ANN forecasting model used an iterative approach in order to provide forecasts up to 6 hours in advance. The ANN model was optimized through an extensive search algorithm. The results are compared with the measurements and forecasts made by the SVR model presented by Le Cam, Daoud, & Zmeureanu (2016). Different approaches for updating the ANN through the use of the sliding window technique are also compared, and the quality of the forecasts are discussed.

METHOD

Forecasting method

The major steps and tasks of the forecasting method are outlined in Table 1 and based on Makridakis, Wheelwright & Hyndman (2003).

Table 1: Forecasting Methodology Overview

Step Number	Definition of Tasks
Step 1: Problem definition	- Literature review - Problem definition - Identification of objectives
Step 2: Data gathering	- Data extraction from BAS
Step 3: Preliminary analysis	- Visualization and preprocessing of data
Step 4: ANN Construction	- Data selection - ANN architecture selection
Step 5: Evaluation of ANN	- Use of the ANN with the testing data
Step 6: Comparison	- Comparison of forecasting methods - Comparison of results from retraining with sliding window techniques

Neural network overview

In the majority of cases, time series are characterized by high variations and rapid transients. This makes modeling a time series with a linear model quite challenging. In such

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cases, nonlinear models are often used. Equation (1) provides the governing equation for the type of ANN used, the nonlinear autoregressive (NAR) neural network. The training of the neural network aims at approximating the unknown function f by using the historical values to tune the weights within the neural network.

$$y(t+1) = f\big(y(t), y(t-1), \dots, y(t-n)\big) + e_t \qquad (1)$$

Where the topology of the NAR is shown in Figure 1.

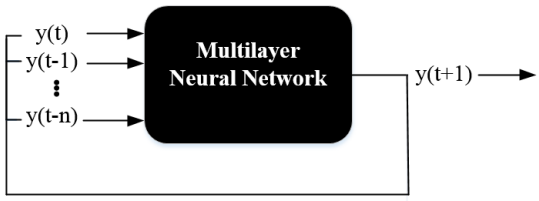

Figure 1: Nonlinear Autoregressive Multilayer Neural Network

In the case of training, an open loop ANN is trained by comparing the inputs (historical data) with the desired output. Training of the ANN is stopped when one of two different criteria have been met: (i) the magnitude of the gradient falls below 1.0e-7, (ii) the maximum amount of iterations is reached.

Once the ANN has been trained, the loop is then closed providing the network feedback from its own predicted values. For example, starting with a trained ANN and known inputs, from (t, to t-5), the ANN will forecast the target variable t+1. The output value of t+1 is then fed back into the ANN as an input (along with values for times, t, t-1,..., t-4) to forecast the next value of t+2. In order to keep a constant number of inputs, once the next forecasted value (t+1) is calculated, it is then used as an input removing the last value from the previous input set (t-5). The iterative process continues until the forecast horizon has been reached.

The performance evaluation indices for the ANN and the SVR models adopted through this paper are the root mean squared error (RMSE) and the coefficient of variation of the root mean squared error CV(RMSE), which are defined as follows (EVO, 2007):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \qquad (2)$$

$$\mathrm{CV(RMSE)} = \frac{\mathrm{RMSE}}{\bar{y}} \qquad (3)$$

where $\hat{y}_i$ is the forecasted value of the supply air flow rate, y_i is the recorded value, and $\bar{y}$ is the average of the recorded values over the selected time period.

CASE STUDY

HVAC system overview

The forecasting method is applied to a research center called the Genome (GE) located at Concordia University in Montreal, Canada. The building has a total floor area of 5,400 m^2, four stories, and includes a basement. Primary cooling equipment includes two large chillers of 900 ton (3,165 kW) capacity that are cooled by two cooling towers each with a 29.8 kW fan. This forms the central/primary cooling system feeding chilled water to several buildings. The chilled water supplied to the GE building is fed into the cooling coils of two air handling units.

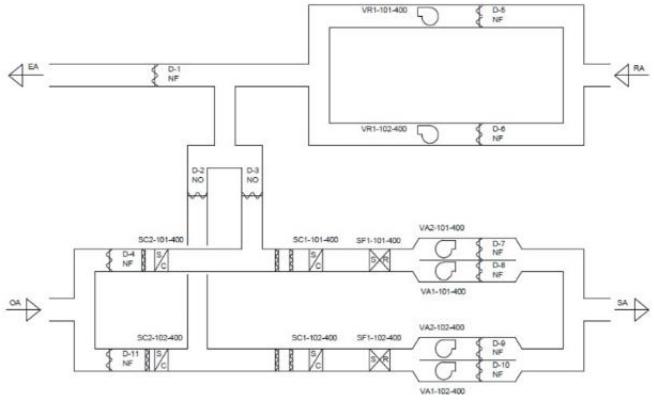

Figure 2: Schematic of HVAC system

The secondary system (Figure 2) contains four supply fans each with a capacity of 10,618 L/s and nominal electric demand of 29.8 kW. These fans supply the conditioned air that satisfies the space cooling needs of the building and usually operate within 39-65% of their total capacity. There are two return fans (15 kW each) that remove air from the offices and conference rooms. In addition, there are two exhaust fans, 30 kW each for ventilation hoods and washrooms.

Exploratory analysis of the supply air flow rate

Figure 3 presents the daily operation of supply fans in both AHUs within a carpet plot. The operation was recorded over the interval of June 1st until August 31st, 2014. The color of each cell represents the supply flow rate as a percentage of the fans total capacity in both AHUs. The dark red color corresponds to the operation of supply fans at about 65% capacity while dark blue corresponds to 0% capacity. The white cells correspond to missing data. The supply fans work at about 40% of their capacity during non-working hours and 50-60% during working hours.

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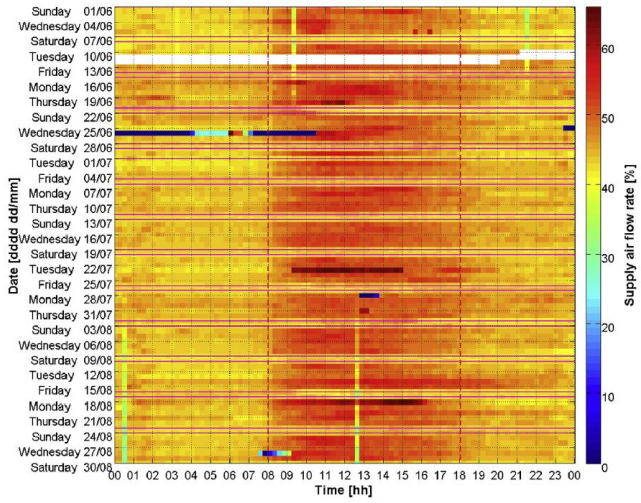

Figure 3: Carpet plot representation of the part load ratio of supply fans in both AHUs (Le Cam, Zmeureanu, & Daoud, 2016)

Pre-processing of data

The preprocessing of data obtained from the BAS includes the identification of missing data, outlier values of erroneous data, and the application of corrective actions. The goal was to have a training data set of 30 days, at 15-minute time steps, corresponding to 2,880 observations of the supply air flow rate. Thus, some additional observations were added in order to compensate for missing data and data removed due to erroneous measurements. Missing data corresponded to "No Data" or "0" values in the BAS trend data and can occur randomly due to faults in the sensors, recording system, or periodic maintenance of the HVAC system. During preprocessing, all missing data were omitted from the training, validation and testing data sets. If four or more consecutive observations had a zero value, the corresponding rows of observations were removed from the data set. If the number of consecutive observations with zero value was less than four, the values were linearly interpolated from the previous and future time steps. Four consecutive observations correspond to one-hour of data. The observations with values outside the typical operating range of 30-80% are defined as outliers (Le Cam, Daoud, & Zmeureanu 2016). Similar to the case of missing data, if four or more consecutive outliers were identified, they were then removed from the data set. Additional observations of the supply flow rate were then added to keep constant the overall amount of the training data set. If less than four consecutive outliers are identified, their values were replaced by linear interpolation of available data before and after the outliers.

Normalization of data

If the value entering the activation function of the neural network is too large or small, it can drive the output of the neuron to zero, one, or infinity depending on which activation function is used. This can cause significant errors and poor performance of the forecasting model. Therefore, the min-max normalization method was used to normalize the data. This method was selected as it is best suited for cases where the bounds are known and not well suited for cases containing lots of variation and outliers (Fausett, 1993). As the boundaries of the supply flow rate are known, the following normalization technique is well suited for this application (Equation 4).

$$x'_k = \frac{x_k - x_{min}}{x_{max} - x_{min}} \quad (4)$$

where x_k is the specific observation in the time series, x_{min} is the minimum value within the time series, and x_{max} is the maximum value.

Neural Network Architecture

Matlab Neural Network toolbox was used in the development of the ANN model. The architecture of the ANN is a crucial factor in the successful application of the forecasting model. Too few connections and the ANN will have limited capabilities (Yao, 1999). Too many connections will result in the ANN learning too much noise in the training data (Yao, 1999). Through an extensive search algorithm applied to the case study presented in this paper, the optimal architecture of the ANN was chosen to be composed of 33 inputs, one hidden layer with four neurons and one output (33-4-1). Varying the length of training days from 1 to 30, input neurons from 1 to 50, and hidden layer neurons, a search was conducted of 36,750 possible scenarios. For comparison, a second neural network composed of 13 inputs, 1 hidden layer neuron, and 1 output neuron was used, which was found to be the optimum architecture in a different case study (Le Cam, Daoud, & Zmeureanu, 2016).

Forecasting Results

This section presents the results of the ANN forecasting model. First, a comparison of the forecasts from the ANN and SVR models are shown. This is then followed by a comparison of results from retraining with sliding window technique.

Forecast-set here refers to a set of six-hour ahead forecasts. For example, F+1 refers to the first forecast-set shown in Figure 4 ranging over the time 9:00, 9:15, 9:30…14:45. As new data becomes available at the next time step (9:00), the forecasting model then uses a new set of inputs and calculates the second forecast-set (F+2) over the time 9:15, 9:30,..,15:00. Within this paper, forecast-sets will use the notation F+x, where x refers to the number of the set.

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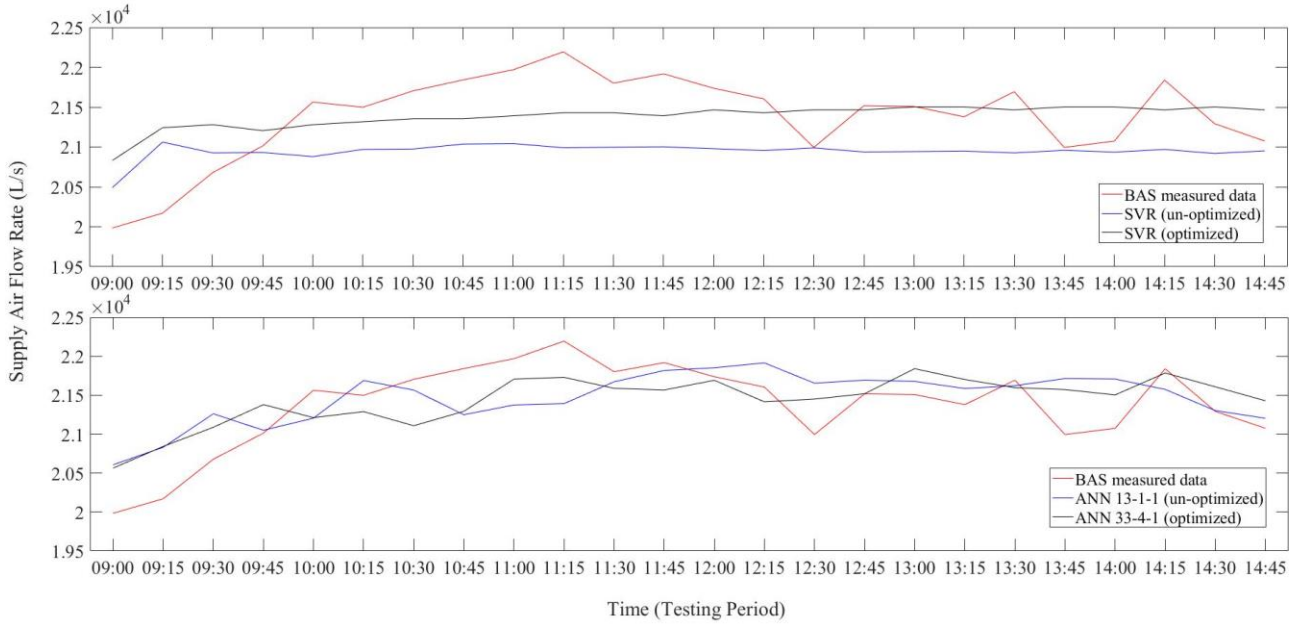

Figure 4: Comparison of the forecast F+1 by ANN and SVR models vs BAS trend data over the forecast horizon of 6-hours

Figure 4 presents F+1 for both SVR and ANN methods. The red line indicates the measured supply air flow rate from the BAS. The top figure depicts the BAS trend data along with the F+1 using the SVR methods previously published by Le Cam et al. (2016). The bottom graph depicts F+1 made using the ANN 13-1-1 and 33-4-1 architectures. From Figure 4, it can be seen that in this example, the ANN forecast follows closer to the trend rather than the SVR iterative forecasting method.

Table 2: Statistical indices for the comparison of forecasting methods

Forecasting Method	RMSE (L/s)	CV(RMSE) (%)
SVR (un-optimized)	724	3.4
SVR (optimized)	463	2.2
ANN-13-1-1 (un-optimized)	427	2.0
ANN-33-4-1 (optimized)	386	1.8

Table 2 provides the performance indices of both forecasting methods for F+1. It can be seen that the ANN models perform similar to the SVR models. The ANN obtained a CV(RMSE) of 1.8-2.0% while the SVR models had and a CV(RMSE) of 2.2-3.4%. It should be noted that the ANN 13-1-1 model performed very well. However, it required more iterations in the assignment of weights during the training and validation phase before adequate results were obtained in comparison to the ANN 33-4-1 model.

In addition to a comparison of forecasting methods, different methods for applying a sliding window were explored. Two approaches were selected: batch retraining and iterative retraining. The batch approach is based on a sliding window that retrains the ANN with a batch of new data samples. For this work, the batch length was equal to the length of the forecast horizon, or 24 sample points. In the iterative approach, retraining occurs once a single new data point becomes available.

For each approach, two separate processes for training would occur: (1) the initialization of the weights would be completely random, and (2) the weights are initialized from the weights of the previous forecasting ANN. Figure 5 provides an overview of the four different scenarios.

The four different scenarios shown in Figure 5 are listed below:

(i) Batch updating with random weight initialization
(ii) Batch updating with weight initialization from weights of previous ANN
(iii) Iterative updating with random weight initialization
(iv) Iterative updating with weight initialization from weights of previous ANN

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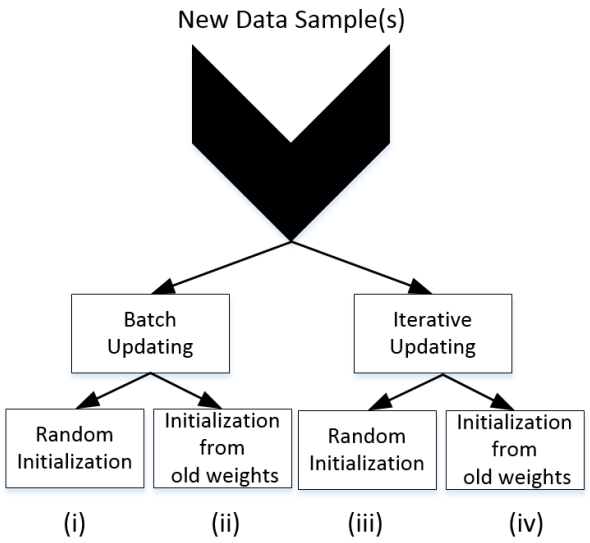

Figure 5: Approaches for implementation of the sliding window technique

For comparison purposes, the testing period was extended from six-hours (24 points) to 12-hours (48 points). For each of the four scenarios shown in Figure 5, forecast-sets were created and recorded. Table 3 presents the average RMSE and CV(RMSE) of each scenario over the 48 forecasted-sets.

Table 3: Statistical indices for application of sliding window over the forecast horizon of 12-hours

	Scenario (i)	**Scenario (ii)**	**Scenario (iii)**	**Scenario (iv)**
Average RMSE over F+1 to F+48 (L/s)	412.70	2,110.40	575.96	736.53
Average CV(RMSE) over F+1 to F+48 (%)	2.05	10.71	2.84	3.67

Table 3 provides the results of the different methods for applying the sliding window. Scenario #i, batch updating and random weight initialization can be seen as having the lowest error with a RMSE of 412.70 L/s and a CV(RMSE) of 2.05%. The scenarios #iii and #iv had also low errors with CV(RMSE) of less than 4%. However, scenario #i offers the advantage of less computational time as retraining is repeated only after 24-time steps, and not after each time step as within the iterative approach.

CONCLUSION

This paper presented the development of a closed loop autoregressive neural network for forecasting the supply air flow rate of an institutional building located in Montreal, Canada. The trend data was recorded on 15-minute time steps and the forecast horizon was 6 hours in advance. The ANN forecasting model was optimized and then compared to an optimized SVR model previously designed. Both SVR and ANN models performed approximately the same with the ANN having a CV(RMSE) of 1.8-2% and the SVR with a CV(RMSE) of 2.2-3.4%. Therefore, it can be concluded that with optimized parameters, both forecasting methods can provide adequate results.

The comparison of sliding window approaches concluded that scenario #i (batch updating and random weight initialization) provided the best results with a CV(RMSE) of 2.05% over the forecast horizon of 12-hours.

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REFERENCES

CEA. (2015, September 12). *Canada's Electricity Industry*. (Canadian Electricity Association) Retrieved September 7, 2016, from Canadian Electricity Association: https://electricity.ca/wp-content/uploads/2017/12/Electricity101_December8_2017.pdf

Chou, J., & Bui, D. (2014). Modeling heating and cooling loads by artificial intelligence for energy-efficient building design. *Energy and Buildings*, 437-446.

De Rocco, S., Aoki, A., & Lamar, M. (2007). Load Forecasting Using Artificial Neural Networks and Support Vector Regression. *International Conference on Power Systems.* Beijing.

EVO. (2007). *International Performance Measurement and Verification Protocol.* Washington: Efficiency Valuation Organization.

Fausett, L. (1993). *Fundamentals of Neural Networks.* London: Pearson.

Kaytez, F., Taplamacioglu, M., Cam, E., & Hardalac, F. (2015). Forecasting electricity consumption: A comparison of regression analysis, neural networks, and least squares support vector machines. *Electrical Power and Energy Systems, 67*(1), 431-438.

ISBN 978-2-921145-88-6

Le Cam, M., Daoud, A., & Zmeureanu, R. (2016). Forecasting electric demand of supply fan using data mining techniques. *Energy*, *101*, 541-557.

Le Cam, M., Zmeureanu, R., & Daoud, A. (2013). Comparison of inverse models used for the forecast of the electric demand of chillers. *International Building Performance Simulation Association.* Chambery.

Le Cam, M., Zmeureanu, R., & Daoud, A. (2016). Cascade-based short-term forecasting method of the electric demand of HVAC system. *Energy*, *119*(1), 1098-1107.

Li, Q., Meng, Q., Cai, J., Yoshino, H., & Mochida, A. (2009). Predicting hourly cooling load in the building: A comparison of support vector machine and different artificial neural networks. *Energy Conversion and Management* , *50*(1), 90-96.

Makridakis, S., Wheelwright, S., & Hyndman, R. (2003). *Forecasting Methods and Applications.* New Jersey: Wiley & Sons.

Neto, A., & Fiorelli, F. A. (2008). Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. *Energy and Buildings*, *40*(2), 2169-2176.

NRCan. *Energy Use Data Handbook.* Natural Resources Canada. Retrieved on (2013, September 20) from http://www.statcan.gc.ca/access_acces/alternative_alternatif.action?teng=57-003-x2016001-eng.pdf&tfra=57-003-x2016001-fra.pdf&l=eng&loc=57-003-x2016001-eng.pdf

Quebec. (2016). *Energy in Quebec a source of growth.* Quebec City : Government of Quebec .

Tang, F., Kusiak, A., & Wei, X. (2014). Modeling and short-term prediction of HVAC system with a clustering algorithm. *Energy and Buildings*, 310-321.

Yao, X. (1999). Evolving Artificial Neural Networks. *Proceedings of the IEEE*, *87*(9), 1423-1477.

ISBN 978-2-921145-88-6