MACHINE LEARNING FOR BUILDING ENERGY MANAGEMENT

HỌC MÁY TRONG QUẢN LÝ NĂNG LƯỢNG TÒA NHÀ

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(Received August 29, 2020; Accepted December 15/11/2020)

Abstract - Future energy use prediction in buildings plays an important role in planning, managing, and saving energy. The complexity of building characteristics and occupants make the energy use prediction difficult. Because of its rapid learning characteristics, this study proposes machine learning (ML) models to predict the building energy consumption. The data set from non-residential buildings was collected to evaluate the predictive performance of the artificial neural network model (ANNs) and the support vector regression model (SVR). The evaluation results showed the effectiveness of the proposed machine learning model in predicting the energy usage during the next 24 hours of the building. The MAPE values obtained by the SVR model was 11.616%. The prediction results provide building managers with a use reference to saving energy consumption. This research contributes to highlight the advantages in the application of machine learning model in the field of construction.

Key words - Machine learning; energy saving; building management

Tóm tắt - Việc dự báo năng lượng sử dụng trong công trình xây dựng đóng vai trò rất quan trọng trong việc lên kế hoạch, quản lý và tiết kiệm năng lượng. Rất khó để đạt được kết quả dự báo chính xác bởi sự phức tạp của các đặc tính công trình và hành vi của người sử dụng năng lượng trong tòa nhà. Bởi đặc tính học nhanh, nghiên cứu này đề xuất sử dụng mô hình học máy (machine learing – ML) làm phương pháp để dự báo năng lượng tiêu thụ của tòa nhà phi dân cư. Bộ dữ liệu từ các tòa nhà phi dân cư được thu thập để đánh giá hiệu suất dự báo của mô hình mạng Nơ-ron nhân tạo (ANNs) và mô hình hồi quy vecto hỗ trợ (SVR). Với việc đánh giá kết quả đạt được, nghiên cứu đã cho thấy tính hiệu quả của mô hình máy học được đề xuất trong việc dự báo năng lượng sử dụng trong 24 giờ tiếp theo của tòa nhà. Mô hình SVR đạt được giá trị sai số giá trị tuyệt đối trung bình (MAPE) là 11.616%. Kết quả dự đoán cung cấp thông tin giúp quản lý và vận hành trong việc tiết kiệm năng lượng tiêu thụ. Nghiên cứu này góp phần làm nổi bật những lợi thế trong việc ứng dụng mô hình máy học trong lĩnh vực xây dựng.

Từ khóa - Học máy; tiết kiệm năng lượng; quản lý tòa nhà

1. Introduction

Saving energy consumption in buildings is one of the key policies for nationals around the word. For example, European energy policies have focused on the enhancement of energy efficiency and the uses of renewable energy sources [1]. The efficient use of natural resources and energy contributes to the improvement of the living environment and keeps the earth from the greenhouse effect and carbon dioxide emissions. Building energy demand comprise a huge proportion of the total energy consumption around the world [2, 3]. For example, commercial and residential buildings consume about 40% of total energy use in the U.S [2, 4]. In addition, during the operational stage, buildings consume energy up to 50 years or more. Thus, buildings are imperative to be designed and operated with respect to energy consumption toward sustainable development.

Energy saving in buildings has attracted the special attention of researchers, designers, and building managers [5, 6]. Predicting energy use in buildings plays an irreplaceable role in energy planning, management, and conservation [7]. Data-driven models for energy consumption prediction in buildings have been comprehensively reviewed by Ferrari et al. [8], Amasyali and El-Gohary [9], Wei et al. [10], Deb et al. [11] Energy consumption in buildings has been predicted using ML models such as the SVR [7], extreme learning machine (ELM) [2, 12], artificial neural networks (ANNs) [13], deep recurrent neural networks (RNN) model [14], generative adversarial nets [15], and gradient boosting machine [16].

The ML models are powerful for predicting building energy patterns such as ANNs, SVR, gradient boosting regression, and ELM. Gao et al. examined the effectiveness of sixteen single ML models such as Random Forest (RF), M5Rule, ANNs, and SVR models in designing energy-efficient residential buildings [17]. Their findings revealed that RF was powerful in predicting cooling load and heating load in buildings. RF, M5Rules, k-nearest neighbor, SVR, and ANNs models were also applied to predict wind power [18].

Although ML models are effective in solving prediction problems, their performance is still limited to identify accurately energy consumption patterns. It is because energy consumption patterns depend non-linearly on building facades, operational schedule, and historical energy data. This complex relationship results in difficulty in the prediction. Thus, improving predictive accuracy and generalization ability is essential.

The aim of this work is to propose the single ML models to predict energy consumption in buildings. For validation, two experimental datasets obtained from two buildings were used to assess the proposed baseline ML models. The predictive accuracy of the proposed model was compared to those of single ML models via statistical indices. This study contributes to highlighting the advantages of ML applications for the building sector.

2. Literature review

Prediction of energy consumption patterns in buildings is extremely vital for energy management and cooperation between building energy and power grid [15]. Chou and

Truong developed a cloud-based energy use prediction system to monitor and alert the status of energy consumption in buildings [19]. A hybrid artificial intelligent model was integrated into their proposed system to improve the accuracy of daily energy use prediction. Their system enables to identify anomalous energy pattern in building in real-time and send a message to the users that can help users in adjusting their energy use.

Various ML models have been investigated performance in predicting cooling load and heating load in buildings [17], which include elastic net (EN), Gaussian process regression (GPR), least median of squares regression (LMSR), multiple linear regression (MLR), multi-layer perceptron regression (MPR), multi-layer perceptron (MLP), radial basis function regression (RBFR), sequential minimal optimization regression (SMOR), functions XNV, lazy K-star, lazy LWL, rules decision table (RDT), M5Rules, alternating model tree (AMT), directional path consistency (DPC), and RF [17].

Naji et al. applied the ELM method for building energy consumption prediction [2]. Building energy consumption data were simulated using EnergyPlus software by hundreds of combinations of material thicknesses and their thermal insulation capability. The comparison results revealed that the EML method was superior to the genetic programming and ANNs in predicting annual energy use. Their study helps architects and engineers in designing sustainable structures based on the optimal characteristics of materials. Their findings highlight the power of computer science applications for the building industry.

Ahmad et al. applied supervised based ML models to predict the total energy demand for power usage in buildings [20]. Four single ML models used in their study include the binary decision tree, compact regression Gaussian process (GP), stepwise GP regression, and generalized linear regression model. ML models also were used to forecast long-term energy commodities prices. The researchers compared the forecast performance of ML models with traditional econometric models using monthly prices [21]. Their findings confirmed the powerful tool of ML an accurate to support policymakers in the international energy market.

Residential and commercial buildings consume a significant amount of the overall energy consumption in the U.S. [14]. Deep recurrent neural networks (RNN) model was used to predict medium-to-long term electricity consumption in commercial and residential buildings [14]. The Public Safety Building in Salt Lake City, Utah and residential buildings in Austin, Texas were used to assess the performance of the RNN model. The analytical results revealed that the performance of the RNN model was better than that of the ANNs model in predicting electricity consumption in commercial buildings. However, the ANNs model was better than that of the RNN model for electricity consumption prediction in residential buildings. Thus, this work aims to investigate this approach in predicting building energy consumption.

3. Research methodology

3.1. Artificial neural networks

ANNs is a classifier that uses backpropagation to learn a multi-layer perceptron to classify instances. A multi-layer perceptron is a feedforward neural network that maps sets of input data onto a set of appropriate outputs. This model consists of an input layer containing a set of sensory input nodes, one or more hidden layers containing computation nodes, and an output layer containing one computation node (Figure 1). Calculate the error between the actual output and the expected output. Depending on the error, adjust the weights by multiplying the error with the input and again with the gradient of the Sigmoid curve.

Equation (1) expresses an activated neuron in a hidden output layer.

$$net_j = \sum w_{ji} x_i \text{ and } y_j = f(net_j) \tag{1}$$

Where, net_j denotes the activation of jth neuron; i denotes the set of neurons in the preceding layer; w_{ji} denotes the weight of the connection between neuron j and neuron i; x_i denotes the output of neuron i; and y_j denotes the sigmoid or logistic transfer function.

$$f(net_j) = \frac{1}{1+e^{-\lambda net_j}} \tag{2}$$

Where, λ controls the function gradient.

The formula for training and updating weights w_{ji} in each cycle h is determined as in Eq. (3).

$$w_{ji}(h) = w_{ji}(h-1) + \Delta_{ji}(h) \tag{3}$$

Here, $\Delta_{ji}(h)$ is the change.

$$\Delta_{ji}(h) = \eta \delta_{pi} \chi_{pi} + \alpha \Delta w_{ji}(h-1) \tag{4}$$

Where, η is the learning rate parameter; δ_{pi} is the propagated error; χ_{pi} is the output of neuron i for record p; α is the momentum parameter; and $\Delta w_{ji}(h\text{-}1)$ is the change in w_{ji} in the previous cycle.

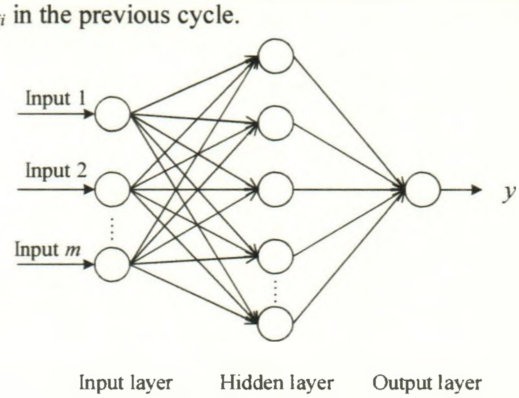

Figure 1. *Graphical structure of ANNs*

3.2. Support vector regression

Support vector regression (SVR) is a regression variation of support vector machines [22] that minimizes an upper bound of the generalization error than minimize the empirical error in neural networks. Figure 2 presents a structure of a support vector regression [23]. In this classifier, an ε-insensitive loss function is used to map nonlinearly the input space into a high-dimensional feature space, and then run linear regression in the output space. The SVR can thus be formulated by simplifying the following function.

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{5}$$

Subject to $y_i - f(x_i, \omega) \le \varepsilon + \xi_i^*$;

$f(x_i, \omega) - y_i \le \varepsilon + \xi_i^*$; $\xi_i, \xi_i^* \ge 0, i = 1, \ldots, n$

Where, ω is the parameter of the linear approximator; $C \ge 0$ is a regularization constant that represents the trade-off between the empirical error and the flatness of the function; ξ and ξ^* are nonnegative slack variables; x_i is input patterns; y_i is prediction labels; and n is the sample size. This optimization problem is converted to a dual problem as Eq. (6)

$$f(x) = \sum_{i=1}^{n_{SV}}(\alpha_i - \alpha_i^*)K(x, x_i) \tag{6}$$

subject to $0 \le \alpha_i^* \le C$; $0 \le \alpha_i \le C$

where, n_{SV} is the number of support vectors and $K(x, x_i)$ is the kernel function. During training, the radial basis function (RBF) kernel is used to identify support vectors along the function surface.

3.3. Dataset and model settings

Table 1 presents two datasets of building energy consumption data that was collected from [25]. Floor areas of buildings 1 and 2 are 5292.6 m^2 and 2918.5 m^2, respectively. One-year dataset in the hourly resolution was used in this study that retrieved from Jan. 2015 to Dec. 2015. The data sample size was 8760 data points for each dataset. The training data was 90% of the sample size and the test data was 10% of the sample size. The training data was to train the ANNs and SVR model and the test data aimed to test the performance of the models.

Table 2 shows inputs and output attributes to evaluate the prediction models. Model inputs include historical energy consumption data, the day of the week, the hour of the day. Table 3 presents the parameter settings of the ANNs and SVR models.

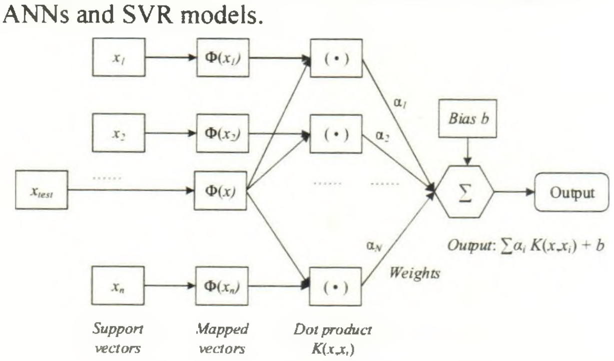

Figure 2. *Graphical structure of SVR*

Table 1. *Dataset*

Building	Name	Primary space usage	Area (m^2)	Location
Building 1	UnivClass_Clifford	College Classroom	5292.6	America/ New York
Building 2	UnivClass_Camden	College Classroom	2918.5	America/ New York

Table 2. *Data attribute*

Symbol	Attribute	Unit	Description
Input			
X1	Day of the week	-	Mon., Tue., Wed., Thur., Fri., Sat., Sun.
X2	Hour of the day	-	0, 1, 2, …, 21, 22, 23
X3	Historical energy consumption	kWh	Numeric values
Output			
Y	Next 24-hour energy consumption	kWh	Numeric values

Table 3. *Model settings*

Model	Parameter settings
ANNs	Hidden layer = *a*, learning rate = 0.3, and momentum = 0.2
SVR	*C* = 1, the RBF kernel, and gamma = 0.01

4. Prediction results

This section analyzed the performance of the ANNs and SVR models in forecasting the next 24-hour energy consumption data in the investigated buildings. the statistical indexes including mean absolute (MAE), mean absolute percentage error – (MAPE), and root mean square error (RMSE) were used to assess the performance of these models.

Tables 4 and 5 revealed the accuracy of ANNs and SVR models for predicting energy data over the training and test phases. Table 4 presented the performance of the ANNs model. The results show that the MAPE values were higher than 10% for all datasets from two buildings. Compared to a performance by the SVR model in Table 5, the MAE values obtained by the ANNs model were higher than those obtained by the SVR model. For example, for buildings 1 and 2, the MAE values were 0.131 kWh, and 1.455 kWh (as shown in Table 4). For providing readers with a comprehensive view, Figure 3 visualized the line plots between the actual energy data and estimated energy data over the training and test phases on building 1.

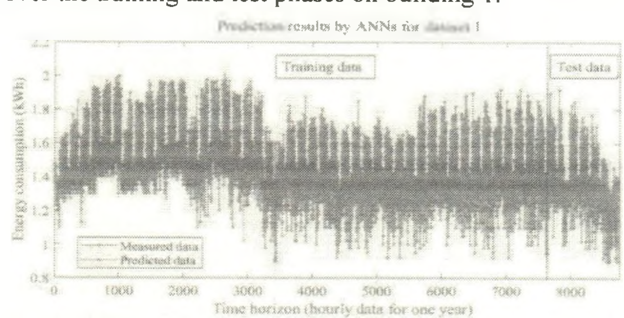

Figure 3. *Prediction results by ANNs over the training and test*

Table 5 presents the MAE, MAPE, and RMSE values obtained by the SVR model for predicting future energy consumption for two experimental buildings. The SVR model obtained quite good accuracy. the average MAE and MAPE over two datasets were 0.639 kWh and 11.616% in the test phase. Particularly, the obtained MAPE values were less than 20%. Notably, the SVR model captured well energy consumption patterns in building 1 with 6.097% in MAPE. Figure 4 compared the predicted and retrieved data in the test phase that obtained by the SVR model. The results show that the SVR model obtained the smaller error with 0.6395 kWh in MAE and 0.932 kWh in RMSE that those of the ANNs model. The SVR model has proved its advance in predicting building energy consumption. The novel model of building energy prediction is capable to analyze the temporal data such as day of the week and hour of the day in the prediction. This improved accuracy of prediction results.

***Table 4.** Performance of ANNs for electricity consumption prediction*

ANNs	Performance in training phase (90%)			Performance in test phase (10%)		
	MAE (kWh)	MAPE (%)	RMSE (kWh)	MAE (kWh)	MAPE (%)	RMSE (kWh)
Building 1	0.103	7.498	0.126	0.131	10.741	0.163
Building 2	1.984	22.866	4.130	1.455	20.208	2.117
Average	1.044	15.182	2.128	0.793	15.475	1.140

***Table 5.** Performance of SVR for electricity consumption prediction*

SVR	Performance in training phase (90%)			Performance in test phase (10%)		
	MAE (kWh)	MAPE (%)	RMSE (kWh)	MAE (kWh)	MAPE (%)	RMSE (kWh)
Building 1	0.080	5.514	0.108	0.077	6.097	0.105
Building 2	1.419	17.543	2.147	1.202	17.135	1.759
Average	0.749	11.5285	1.127	0.639	11.616	0.932

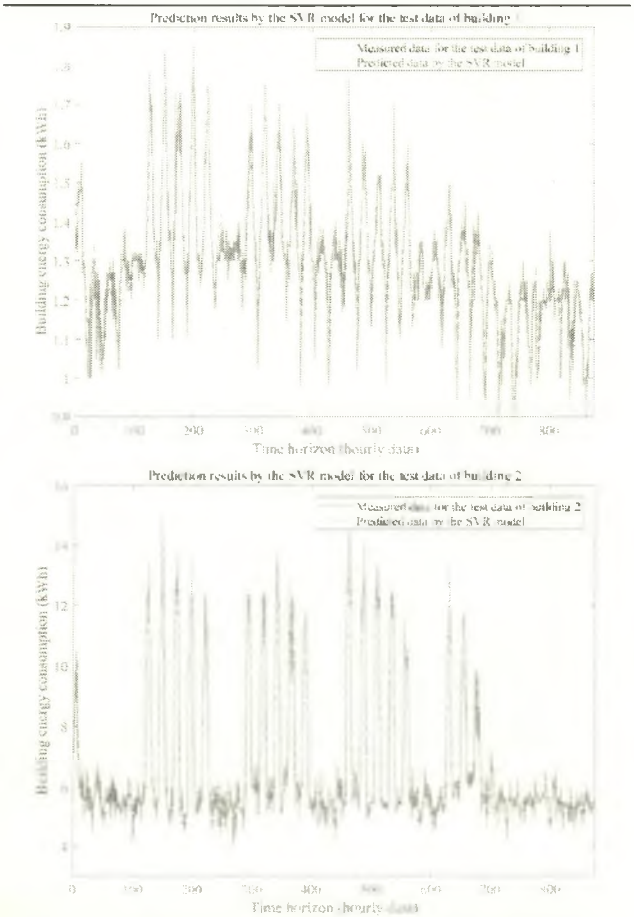

***Figure 4.** Plots of measured data and predicted data that obtained by the SVR model*

5. Conclusions

This work aims to propose ML models for forecasting energy consumption in non-residential buildings. Two datasets from non-residential buildings were used to assess the predictive performance of artificial neural networks and support vector regression. The analytical results show that the SVR model obtained quite good accuracy in building energy consumption prediction rather than ANNs model. The average MAE and MAPE values obtained by the SVR model were 0.639 kWh and 11.616%. For the ANNs model, the average MAE, MAPE, and RMSE values obtained by the ANNs model were 0.793 kWh, 15.475%, and 1.140 kWh, respectively. The comparison results show that the proposed the SVR model obtained the smaller error. These low values of errors depicted the good predictive accuracy of the SVR model in predicting building energy consumption.

Thus, the SVR models can be proposed as a potential method for forecasting energy consumption in buildings. This study contributes to boost ML applications for the building sector. As a limitation of this study, parameters of the ML models were set as default that may limit their predictive accuracy. From the perspective of practical engineering applications, the model performance should be evaluated from multiple perspectives such as generalization and robustness in future works.

Acknowledgment: This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 102.05-2019.01.

REFERENCES

[1] D'Agostino D, Cuniberti B, Bertoldi P. Energy consumption and efficiency technology measures in European non-residential buildings. *Energy and Buildings*. 2017;153:72-86.

[2] Naji S, Keivani A, Shamshirband S, Alengaram UJ, Jumaat MZ, Mansor Z, et al. Estimating building energy consumption using extreme learning machine method. *Energy*. 2016;97:506-16.

[3] Chou J-S, Tran D-S. Forecasting energy consumption time series using machine learning techniques based on usage patterns of residential householders. *Energy*. 2018;165:709-26.

[4] Bokalders V, M. B. The whole building handbook-how to design healthy, efficient and sustainable buildings. London: Earthscan; 2010.

[5] Zhang X-H, Zhu Q-X, He Y-L, Xu Y. Energy modeling using an effective latent variable based functional link learning machine. *Energy*. 2018;162:883-91.

[6] Chou JS, Ngo NT, Chong WK, Gibson GE. 16 - Big data analytics and cloud computing for sustainable building energy efficiency. In: Pacheco-Torgal F, Rasmussen E, Granqvist C-G, Ivanov V, Kaklauskas A, Makonin S, editors. Start-Up Creation: Woodhead Publishing; 2016. p. 397-412.

[7] Zhong H, Wang J, Jia H, Mu Y, Lv S. Vector field-based support vector regression for building energy consumption prediction. *Applied Energy*. 2019;242:403-14.

[8] Ferrari S, Zagarella F, Caputo P, D'Amico A. Results of a literature review on methods for estimating buildings energy demand at district level. *Energy*. 2019;175:1130-7.

[9] Amasyali K, El-Gohary NM. A review of data-driven building energy consumption prediction studies. *Renewable and Sustainable Energy Reviews*. 2018;81:1192-205.

[10] Wei Y, Zhang X, Shi Y, Xia L, Pan S, Wu J, et al. A review of data-driven approaches for prediction and classification of building

energy consumption. *Renewable and Sustainable Energy Reviews*. 2018;82:1027-47.

[11] Deb C, Zhang F, Yang J, Lee SE, Shah KW. A review on time series forecasting techniques for building energy consumption. *Renewable and Sustainable Energy Reviews*. 2017;74:902-24.

[12] Geng Z, Li H, Zhu Q, Han Y. Production prediction and energy-saving model based on Extreme Learning Machine integrated ISM-AHP: Application in complex chemical processes. *Energy*. 2018;160:898-909.

[13] Chaudhuri T, Soh YC, Li H, Xie L. A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings. *Applied Energy*. 2019;248:44-53.

[14] Rahman A, Srikumar V, Smith AD. Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. *Applied Energy*. 2018;212:372-85.

[15] Tian C, Li C, Zhang G, Lv Y. Data driven parallel prediction of building energy consumption using generative adversarial nets. *Energy and Buildings*. 2019;186:230-43.

[16] Touzani S, Granderson J, Fernandes S. Gradient boosting machine for modeling the energy consumption of commercial buildings. *Energy and Buildings*. 2018;158:1533-43.

[17] Gao W, Alsarraf J, Moayedi H, Shahsavar A, Nguyen H. Comprehensive preference learning and feature validity for designing energy-efficient residential buildings using machine learning paradigms. *Applied Soft Computing*. 2019;84:105748.

[18] Taslimi Renani E, Elias MFM, Rahim NA. Using data-driven approach for wind power prediction: A comparative study. *Energy Conversion and Management*. 2016;118:193-203.

[19] Chou J-S, Truong N-S. Cloud forecasting system for monitoring and alerting of energy use by home appliances. *Applied Energy*. 2019;249:166-77.

[20] Ahmad T, Chen H, Huang R, Yabin G, Wang J, Shair J, et al. Supervised based machine learning models for short, medium and long-term energy prediction in distinct building environment. *Energy*. 2018;158:17-32.

[21] Herrera GP, Constantino M, Tabak BM, Pistori H, Su J-J, Naranpanawa A. Long-term forecast of energy commodities price using machine learning. *Energy*. 2019;179:214-21.

[22] Vapnik VN. *The nature of statistical learning theory*. New York: Springer-Verlag; 1995.

[23] Chou J-S, Ngo N-T, Pham A-D. Shear Strength Prediction in Reinforced Concrete Deep Beams Using Nature-Inspired Metaheuristic Support Vector Regression. *Journal of Computing in Civil Engineering*. 2016;30.

[24] Wang H, Hu D. Comparison of SVM and LS-SVM for regression. International Conference on Neural Networks and Brain: *IEEE*; 2005. p. 279-83.

[25] Miller C, Meggers F. The Building Data Genome Project: An open, public data set from non-residential building electrical meters. Energy Procedia. 2017;122:439-44.