Hybrid machine learning for time-series energy data for enhancing energy efficiency in buildings

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Abstract. Buildings consume about 40 percent of the world's energy use. Energy efficiency in buildings is an increasing concern for the building owners. A reliable energy use prediction model is crucial for decision-makers. This study proposed a hybrid machine learning model for predicting one-day-ahead time-series electricity use data in buildings. The proposed SAMFOR model combined support vector regression (SVR) and firefly algorithm (FA) with conventional time-series seasonal autoregressive integrated moving average (SARIMA) forecasting model. Large datasets of electricity use in office buildings in Vietnam were used to develop the forecasting model. Results show that the proposed SAMFOR model was more effective than the baselines machine learning models. The proposed model has the lowest errors, which yielded 0.90 kWh in RMSE, 0.96 kWh in MAE, 9.04 % in MAPE, 0.904 in R in the test phase. The prediction results provide building managers with useful information to enhance energy-saving solutions.

Keywords: Energy consumption data, Machine learning, Data analytics, Prediction model.

1 Introduction

Buildings consumes about 40 percent of the world's energy use and 30 percent of carbon dioxide generation [1, 2]. Saving electricity consumption in buildings is valuable [3]. Energy-saving solutions in buildings have been attracted concerns of various researches [4]. Forecasting future energy consumption can provide a reference for users or building managers to save their energy use. Future energy data prediction is a method of projecting future data based on historical time-series data.

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Building energy data is recognized as time-series data that vary along with hourly or daily - based timestamps. Statistics-based methods and machine learning (ML) methods have been developed for predicting time-series data. An autoregressive integrated moving average (ARIMA) is an example of powerful statistical methods [5]. However, ARIMA models are suitable for modeling the linear relationship between inputs and outputs.

Energy consumption prediction is difficult because it is affected uncertainly by occupant`s behaviors [6]. Because the nature of the energy use exhibits the complex and seasonal pattern, the unreliable forecast may result in an additional production or waste of resources [7]. Meanwhile, machine learning (ML) have been increasingly used in various domains [8]. Prediction models were developed based on a single machine learning model, ensemble ML models such as XGboost, the feedforward deep networks (FDN) [9], and hybrid ML models [10].

Artificial neural networks (ANNs) models were used to forecast building electricity consumption [11]. The integration of ANNs and ARIMA models was proposed for predicting time-series data [12]. Support vector regression (SVR) was used to forecast the hourly cooling energy demand in office buildings [13]. The SVR was combined with the genetic algorithm (GA) to forecast energy use [14]. However, the SVR is relatively slow in dealing with huge data [15] and a high computational burden [16]. The least-squares support vector regression (LSSVR) [17] is also widely used for prediction problems because it can reduce the computational effort [18].

Pham et al. (2020) proposed the random forests (RF)– based ML model for forecasting short-term electricity use patterns in buildings [4]. Ngo (2019) has investigated the effectiveness of various single and ensemble approaches for building energy simulation and prediction [19]. Although ML models have been used to develop prediction models in previous works, few studies have used a hybrid approach. This study proposed a hybrid machine learning model to predicting one-day-ahead energy use in office buildings. The proposed model combined the SARIMA model, the LSSVR model, and the firefly algorithm (FA). The proposed hybrid ML model can learn the linear and nonlinear patterns in energy data. The model can involve the temporal data and weather data, and historical energy data as the inputs. Energy consumption data in Vietnam was used to evaluate the proposed model.

2 Hybrid Machine Learning Model

2.1 SARIMA Model

Seasonal AR and MA terms in the SARIMA model predict energy consumption in building y_t by using data values and errors at previous periods with lags that are multiples of the seasonality length S. The SARIMA(p, d, q) × (P, D, Q)$_S$, is a multiplicative model that consists of nonseasonal and seasonal elements. Equation (1) presents the mathematical expression of the SARIMA model as described in [20, 21]. The terms of the model are expressed in Eqs. (2)–(5) [5].

$$\theta_p(B)\Theta_P(B^S)(1-B)^d(1-B^S)^D y_t = w_q(B)W_Q(B^S)\alpha_t \quad (1)$$

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$$w_q(B) = 1 - w_1 B - w_2 B_2 - w_3 B^3 - \ldots - w_q B^q \tag{2}$$

$$\theta_p(B) = 1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3 - \ldots - \theta_p B^p \tag{3}$$

$$\Theta_P(B^S) = 1 - \Theta_1(B^S) - \Theta_2(B^{2S}) - \Theta_3(B^{3S}) - \ldots - \Theta_P(B^{PS}) \tag{4}$$

$$W_Q(B^S) = 1 - W_1(B^S) - W_2(B^{2S}) - W_3(B^{3S}) - \ldots - W_Q(B^{QS}) \quad 5)$$

where p is the nonseasonal AR; d is nonseasonal differencing; q is the nonseasonal MA; P is the seasonal AR; D is seasonal differencing; Q is the seasonal MA order; S is the season length; B is the backward shift operator; $w_q(B)$, $\theta_p(B)$, $\Theta_P(B^S)$, and $W_Q(B^S)$ are polynomials in B; y_t is the actual value at the time t; α_t is the estimated residual at the time t; d, q, P, D, Q are integers.

2.2 Support Vector Regression Model

LSSVR models were developed [17] to deal with the large data sets. During the training phase, the least squares cost function was used to get a linear set of equations in a dual space. Then, the conjugate gradient method is used to derive a solution by efficiently solving a set of linear equations [22]. Given a training data set $\{x_k, y_k\}_{k=1}^{N}$, function estimation using LSSVR is formulated as an optimization problem, as expressed in the Eq. (6):

$$\min_{\omega,b,e} J(\omega,e) = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{k=1}^{N} e_k^2 \text{; subject to } y_k = \langle \omega, \varphi(x_k) \rangle + b + e_k, \quad k = 1,\ldots N \tag{6}$$

where $J(\omega,e)$ denotes the optimization function, ω denotes the linear approximator parameter, $e_k \in R$ denote error variables, $C \geq 0$ denotes a regularization constant specifying the constant representing the trade-off between empirical error and function flatness, x_k denotes input patterns, y_k denotes prediction outputs, and N denotes the sample size.

The resulting LSSVR model for function estimation is expressed as Eq. (7).

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{7}$$

where α_k, b denote the Lagrange multipliers and the bias term, respectively, and $K(x,x_k)$ denotes the kernel function. The Gaussian radial basis function (RBF) in the LSSVR model is expressed mathematically in Eq. (8)

$$K(x,x_k) = \exp(-\|x - x_k\|^2 / 2\sigma^2) \tag{8}$$

where σ is the RBF width.

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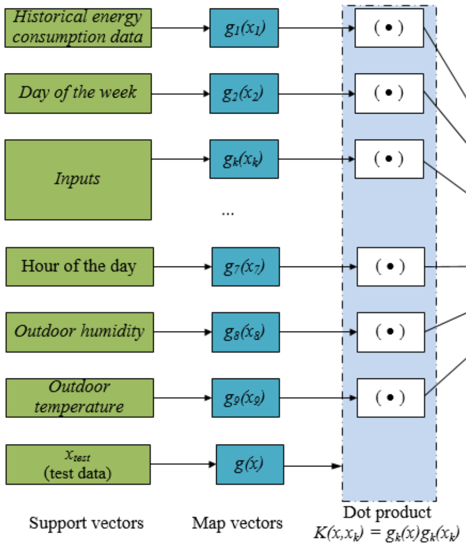

Fig. 1. Structure of SVR model for regression.

2.3 Firefly – based Optimization Algorithm

A firefly algorithm is a nature-inspired metaheuristic algorithm [23]which is potential to identify the global solution and local solution. The FA operation is based on three main principles: a firefly is attracted to other fireflies; the brightness of fireflies impacts its attractiveness regarding the distance among fireflies, and the brightness is affected by the search space of the optimization problems. The attractiveness of a firefly β can be expressed as Eq. (9). The distance between fireflies i and j is calculated as Eq. (10):

$$\beta = \beta_0 e^{-\gamma r^2} \tag{9}$$

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{10}$$

where β is the attractiveness of a firefly; β_0 is the attractiveness at $r = 0$; r is the distance between the firefly and other fireflies; e is a constant coefficient; γ is the absorption coefficient; r_{ij} is the distance between any fireflies i and j at x_i and x_j, respectively; $x_{i,k}$ is the kth component of the spatial coordinate x_i of the ith firefly; $x_{j,k}$ is the kth component of the spatial coordinate x_j of the jth firefly; and d is the number of dimensions in the search space.

An optimal solution is affected by the movement of fireflies during the optimization process. The movement of a firefly is expressed as Eq. (11)

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha^t \theta_i^t \tag{11}$$

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where x_i^{t+1} is the position of the ith firefly; x_i^t is the position of the ith firefly; x_j^t is the position of the jth firefly; α^t is a randomization parameter; and θ_i^t is random numbers.

To improve the performance of the FA, this study adopted the modified version of FA that was developed by Chou and Ngo [24]. A Gauss/mouse map was applied to change an attractiveness parameter while a logistic map in the modified FA generates a diverse population of fireflies. The adaptive inertia weight (AIW) was adopted to vary the randomization parameter α, which can improve the local exploitation and the global exploration during the progress of the optimization process. Moreover, Lévy flights facilitate local exploitation. Figure 2 reveals the pseudocode of the modified FA.

Begin
Define objective function $f(x)$, $x = (x_1, \ldots, x_d)^T$
Set search space and iterations number
Fireflies population is generated by logistic chaotic map x_i ($i = 1, 2, \ldots, n$)
Light intensity I_i at x_i is determined by $f(x_i)$
Define the light absorption coefficient
Initial generation, $t = 0$
while ($t \leq$ maximum iteration) **do**
  Vary value of α using AIW
  Tune value of β using Gauss/mouse chaotic map
    for $i = 1: n$
      for $j = 1: n$
if (*light intensity j> light intensity i*)
  Firefly i moves to firefly j using Eq. (11) with the addition of Lévy flight;
end if
        *Calculate attractiveness with distance r via exp[-γ*r]*
        Evaluate new solutions and update light intensity
end for *j*
end for *i*
    Rank and confirm the current optimum
end while
Export optimal solutions
End

Fig. 2. Pseudocode of modified firefly algorithm.

2.4 Proposed hybrid machine learning model

Figure 3 depicts the two-stage flowchart of the proposed model in predicting time-series energy consumption in buildings. The energy data consists of linear and nonlinear parts, as shown in Eq. (12). In the first stage, the historical energy data was input to the linear SARIMA model to infer the linear building energy consumption data. In the second stage, the nonlinear FA-SVR was used to forecast the nonlinear building energy consumption.

$$Y_t = L_t + N_t \tag{12}$$

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where Y_t represents the building energy consumption data, L_t and N_t represent the linear part and the nonlinear part in building energy consumption data, respectively.

Eq. (13) depicts the predictive results obtained by the SARIMA model in which the linear part in building energy consumption data is modeled as the predicted building energy consumption ($\hat{L}_t$) and residual values o (R_t). As shown in Fig. 3, the inputs in the 1st stage are only historical building energy consumption data.

$$L_t = \hat{L}_t + R_t \tag{13}$$

where $\hat{L}_t$ are the forecasted values by the SARIMA model and R_t are the residual values.

The final prediction results of future building energy consumption were performed in the 2nd stage by the FA-SVR model. Inputs for this stage consists of the forecasted values $\hat{L}_t$, historical building energy consumption, temporal data (i.e., day of the week – DoW and hour of the day – HoD), and weather data (i.e., outdoor temperature and humidity data). Therefore, the forecasted results of building energy consumption were presented as Eq. (14)

$$Y_t = (DoW_t, HoD_t, T_t, H_t, \hat{L}_t, Y_{t-1}, Y_{t-2}, ..., Y_{t-lag}) \tag{14}$$

where DoW_t is the day of the week; HoD_t is the hour of the day; T_t is outdoor temperature; H_t is outdoor humidity data; Y_{t-1} *is* building energy consumption value at the time *t-1;* Y_{t-lag} is the time *(t-lag).*

The nonlinear time-series prediction model was built based on the integration of the SVR model and the FA optimization algorithm (SVR-FA). This integration can significantly improve the predictive performance of the proposed model because the configuration of the SVR model was optimized automatically to fit with data patterns.

The proposed model was experienced the learning phase and test phase using various data sets from real-world buildings. Particularly, the proposed model was learned and tested multiple times. During an evaluation, the learning data were to build the time-series prediction model for building energy consumption in the learning phase.

The SARIMA projected the predicted linear building energy consumption in the 1st stage based on the learning data. At the 2nd stage, the proportion of learning data (i.e., 70% of the total size of the learning data) was applied to train the SVR model while the remaining proportion of the learning data (i.e., 30%) was used to optimize the predictive accuracy of the proposed model via the optimization process by the FA. The FA optimized the optimal hyperparameters of the SVR in the search space via the objective function. In this study, the root-mean-square error (RMSE) was used as the OF for the optimization problem. The RMSE was calculated upon the collected actual building energy consumption data and predicted building energy consumption data. After the learning phase, the learned predicted model was produced. The accuracy of the learned model was tested in the test phase. The test data include the 24-hour building energy consumption data.

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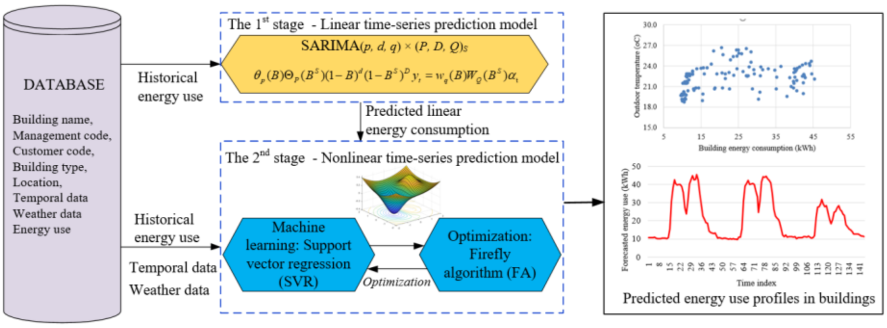

Fig. 3. Flowchart of the proposed SAMFOR model.

3 Dataset and Model Evaluation Results

3.1 Dataset

30-minute energy consumption data and weather data were collected from three office buildings in Vietnam. in years of 2018 and 2019. Each dataset consists of 35,040 data points. Three buildings were selected to test model accuracy. Their energy use profiles for the years of 2018 and 2019 were plotted in Fig. 4. Table 1 summaries the descriptive analysis of these data. These buildings are office buildings. Building 1 is a software development center while building 2 is for a logistic company. Building 3 is working space for a construction company in Danang. The energy use of these buildings is mainly from the air-conditioning system, lighting, and electric appliances.

Table 1. Data description of case studies.

Dataset	30-minutely energy consumption Y (kWh)				Outdoor temperature T (°C)			
	Min	Ave.	Max	Std. dev.	Min	Ave.	Max	Std. dev.
Office building 1	1.74	35.08	144.79	31.49	15.5	27.1	39.3	3.9
Office building 2	0.00	7.25	21.23	2.63	15.5	27.1	39.3	3.9
Office building 3	0.06	4.15	30.10	4.30	15.5	27.1	39.3	3.9

3.2 Model Evaluation Results

The SARIMA model was set as SARIMA (1, 0, 1) × (48, 0, 48)$_{48}$. The seasonal length was set as 48 which consists of a recorded number of data points in a day. The search space for C and σ were set in the range of [10^{-3} 10^{12}]. The firefly's population and maximum iteration were set at 50 and 25, respectively. The proposed model was evaluated 12 times using learning data and test data as shown in Table 2.

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Table 2. Data settings for evaluations of all buildings.

Evaluation	Learning data (4-month historical data)	Test data (one-day-ahead data)
1	January 8 – May 7, 2018	May 8, 2018 (Tuesday)
2	June 15 – October 14, 2018	October 15, 2018 (Monday)
3	April 1 - July 31, 2019	August 1, 2019 (Thursday)
4	August 27 – Dec. 26, 2019	December 27, 2019 (Friday)

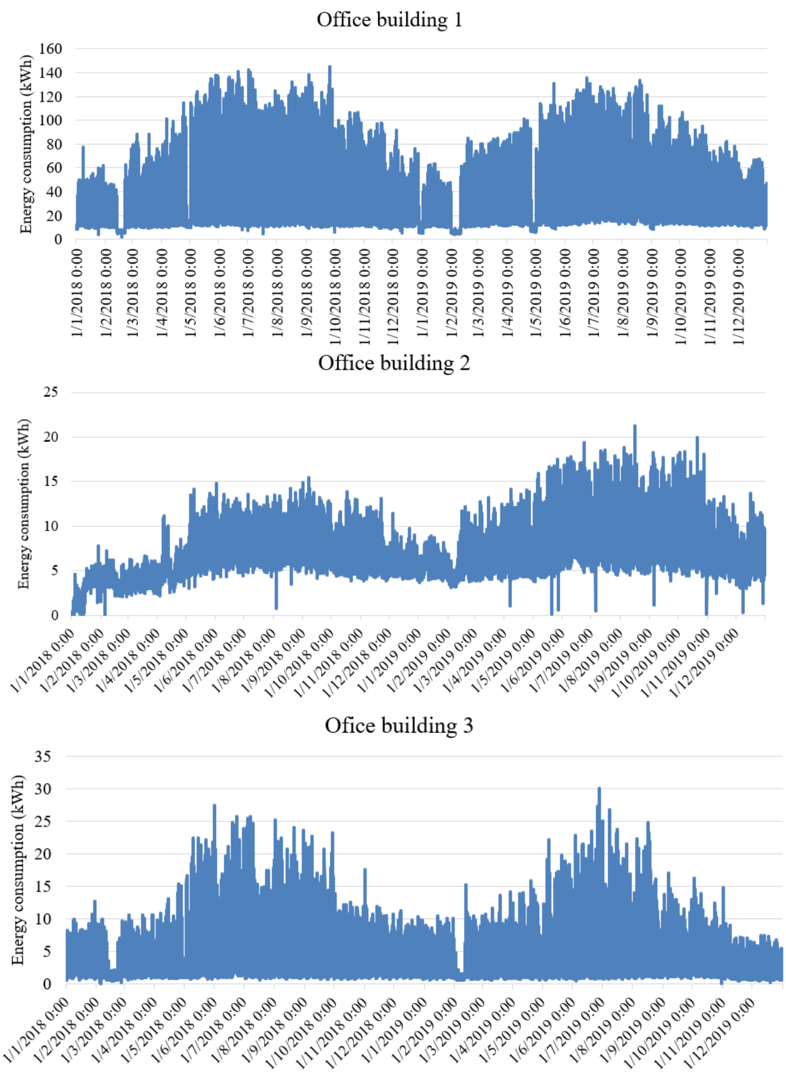

Fig. 4. Energy consumption in the buildings in the years of 2018 and 2019.

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Table 3 depicts the accuracy achieved by the proposed hybrid SAMFOR model. In the learning phase, the average accuracy in three office buildings were 0.89 kWh in mean-square-error (RMSE), 0.91 kWh in mean absolute error (MAE), 10.28 % in the mean absolute percentage error (MAPE), 0.975 in the correlation coefficient (R). In the test phase, the hybrid machine learning model yielded 0.90 kWh in RMSE, 0.96 kWh in MAE, 9.04 % in MAPE, 0.904 in R. Figure 5 visualizes the actual energy data and predicted energy data obtained by the SAMFOR. The results revealed that the proposed model was effective in predicting 30-hourly consumed energy data in office buildings. The SAMFOR model was performed in a desktop with the Intel (R) Core (TM) i7-9750H CPU and the RAM of 8.00 GB. The running CPU time was about 1 minute. Running time of the SVR model was 26 seconds while that of SARIMA was 20 seconds.

Table 3. Performance results by SAMFOR model for three office buildings in the learning phase and test phase.

Dataset	Evaluation	Accuracy by SAMFOR in learning phase				Performance by SAMFOR in test phase			
		RMSE (kWh)	MAE (kWh)	MAPE (%)	R	RMSE (kWh)	MAE (kWh)	MAPE (%)	R
Office building 1	1	1.24	1.54	6.77	0.993	1.69	2.86	5.95	0.996
	2	1.54	2.36	6.63	0.995	1.40	1.97	5.20	0.996
	3	1.39	1.94	5.76	0.996	1.44	2.08	4.45	0.996
	4	1.27	1.61	5.22	0.995	1.11	1.23	3.65	0.995
	Average	1.36	1.86	6.10	0.995	1.41	2.04	4.81	0.996
Office building 2	1	0.51	0.26	24.19	0.960	0.71	0.50	6.43	0.922
	2	0.64	0.41	5.17	0.933	0.55	0.30	4.87	0.904
	3	0.71	0.50	8.48	0.953	0.71	0.50	7.25	0.782
	4	0.70	0.49	7.09	0.958	0.48	0.23	4.19	0.955
	Average	0.64	0.42	11.23	0.951	0.61	0.38	5.69	0.891
Office building 3	1	0.59	0.34	13.73	0.975	0.88	0.77	14.71	0.986
	2	0.76	0.58	13.57	0.983	0.54	0.29	28.92	0.407
	3	0.74	0.55	14.03	0.983	0.79	0.62	13.19	0.966
	4	0.57	0.33	12.71	0.975	0.47	0.22	9.65	0.946
	Average	0.67	0.45	13.51	0.979	0.67	0.48	16.62	0.827
Overall average		0.89	0.91	10.28	0.975	0.90	0.96	9.04	0.904
Std. dev.		0.36	0.74	5.62	0.020	0.42	0.88	7.20	0.168

In Table 4, performance of the proposed SAMFOR model was compared against the SARIMA and SVR models. Scatter plots of actual and predicted energy data produced by the SAMFOR, SARIMA, and SVR models were presented in Fig. 6. For predicting energy consumption in office buildings, the SARIMA model obtained 44.08 kWh in RMSE, 36.94 kWh in MAE, 59.19 % in MAPE, and 0.806 in R. The SVR model was better than the SARIMA model, which yielded 11.70 kWh in RMSE, 5.78 kWh in MAE, 9.89 % in MAPE, and 0.909 in R. Comparison results show that

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the SAMFOR model was more effective than the SARIMA and SVR models in forecasting 30-minute energy consumption in office buildings. The proposed model has the lowest errors with 0.90 kWh in the RMSE, 0.96 kWh in the MAE, and 9.04 % in the MAPE. The hybrid machine learning model enhanced significantly the predictive accuracy compared to other investigated models. Therefore, SAMFOR model was suggested as a forecasting model in predicting energy consumption in office buildings.

Table 4. Performance comparison among base models and proposed model.

Prediction model	Accuracy measures			
	RMSE (kWh)	MAE (kWh)	MAPE (%)	R
SARIMA	44.08	36.94	58.19	0.806
SVR	11.70	5.78	9.89	0.909
Proposed SAMFOR	0.90	0.96	9.04	0.904

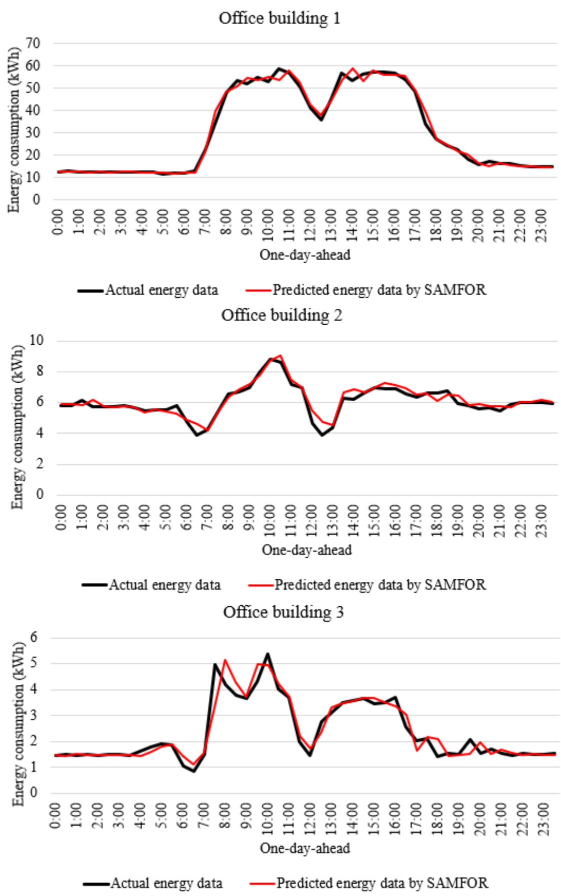

Fig. 5. Actual and predicted energy data by the SAMFOR for office buildings.

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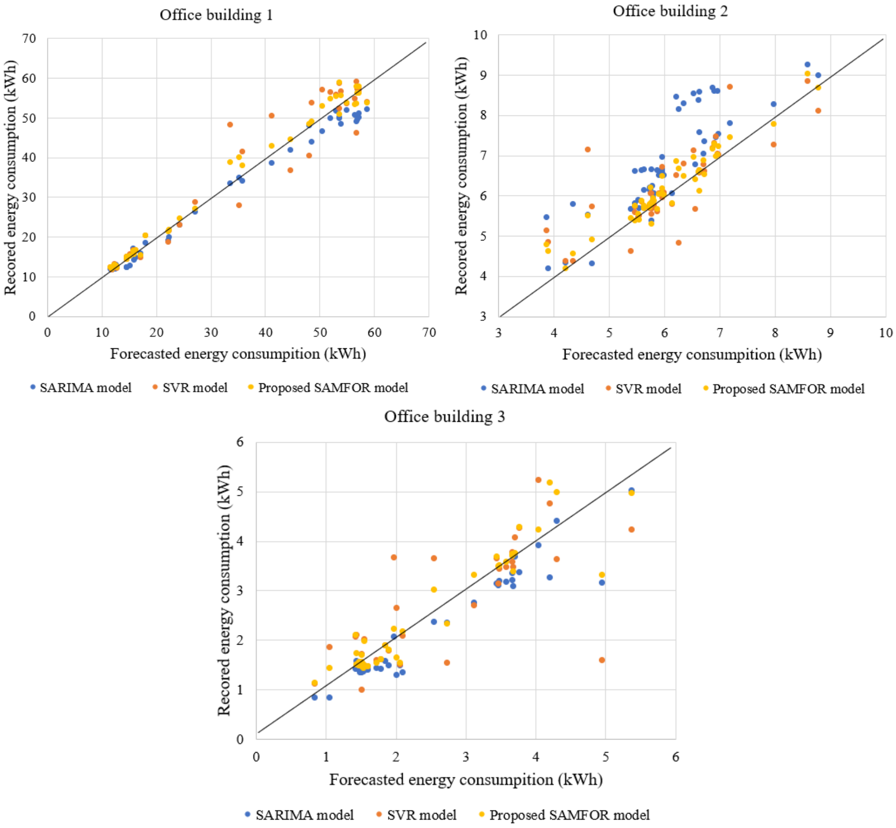

Fig. 6. Scatter plots of actual and predited data by comparing models.

4 Conclusions

This study proposed a hybrid machine learning forecasting model for forecasting energy consumption in office buildings. The proposed SAMFOR model was developed based on the SARIMA, SVR, and FA. A large dataset of 30-minute energy consumption from three office buildings in Vietnam was applied to develop and evaluate the proposed model. the hybrid machine learning model yielded 0.90 kWh in RMSE, 0.96 kWh in MAE, 9.04 % in MAPE, 0.904 in R in the test phase.

Performance of the proposed SAMFOR model was compared against the SARIMA and SVR models. Comparison results show that the SAMFOR model was more effective than the SARIMA and SVR models in forecasting 30-minute energy consumption in office buildings. Therefore, SAMFOR model was suggested as a forecasting model in predicting energy consumption in office buildings.

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The contribution of the study was the effective prediction model in forecasting the one-day-ahead energy data in office buildings. The power of the hybrid approach comes from taking advantages of a linear model and a nonlinear model, in which an optimization algorithm was applied to fine tune the configuration of the proposed model. The predicted results provide building managers and users with useful information to enhance effectiveness of energy use in office buildings. Future studies may perform a comparative analysis between the proposed model and other deep learning models such as a convolutional neural network. Besides, sensitivity analysis on the model parameters should be studied in the future to provide more convincible prediction results.

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