International Journal of Reconfigurable and Embedded Systems (IJRES)
Vol. 14, No. 1, March 2025, pp. 265~272
ISSN: 2089-4864, DOI: 10.11591/ijres.v14.i1.pp265-272

Analysing feature selection: impacts towards forecasting electricity power consumption

Azman Ab Malik[1], Lyu Tao[1], Noormadinah Allias[2], Irni Hamiza Hamzah[3]
[1]School of Computer Science, Universiti Sains Malaysia, Gelugor, Malaysia
[2]School of Computing Sciences, College of Computing, Informatics and Mathematics, Universiti Teknologi MARA, Shah Alam, Malaysia
[3]Electrical Engineering Studies, College of Engineering, Universiti Teknologi MARA, Cawangan Pulau Pinang, Malaysia

Article Info

Article history:

Received Mar 27, 2024
Revised Oct 3, 2024
Accepted Oct 18, 2024

Keywords:

Coefficient of determination
Extreme gradient boosting
Forecasting model
K-nearest neighbor
Machine learning algorithm
Random forest
Support vector regressor

ABSTRACT

This study focuses on the development of electrical power forecasting based on electricity usage in Wuzhou, China. To develop a forecasting model, the important features need to be identified. Therefore, this study investigates the performance of the feature selection method, focusing on the mutual information as a filter and random forest as a wrapper-based feature selection. From the experiment, six features have been chosen, whereby both feature selection methods chose almost identical features. Later, the selected features are trained and tested with common machine learning models, namely random forest regressor, support vector regression (SVR), k-nearest neighbor (KNN) regressor, and extreme gradient boosting (XGBoost) regressor. The performances of the feature selections tested on each of the models are measured in terms of mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2). Findings from the experiment revealed that XGBoost outperform the other machine learning models with RMSE 0.9566 and R^2 indicated with 0.2561. However, SVR outperformed XGBoost and other model by obtaining MAE 0.6028. It can be concluded that the performance of filter-based outperformed the embedded feature selection.

Corresponding Author:

Noormadinah Allias
School of Computing Sciences, College of Computing, Informatics and Mathematics
Universiti Teknologi MARA
Shah Alam, Malaysia
noormadinah@tmsk.uitm.edu.my

1. INTRODUCTION

Artificial intelligent (AI) and internet of thing (IoT) are revolutionizing the management and operation of power grids. Power grids have been improved by enhancing their efficiency, reliability, and adaptability. Modern electrical grid has their capabilities by interconnect IoT technology. IoT sensors placed throughout the power grid continuously collect data on various parameters such as voltage, current, temperature, and equipment status. This data is crucial for real-time monitoring of the grid's health and performance. Power grids are complex networks that transport electricity from power plants to consumers. As industry and households grow, the demand for electrical energy is expected to gradually increase. As a result, power distribution companies need to efficiently plan the allocation of their resources to anticipate the demand period, plan for contingencies and efficiently manage network congestion. This will not only assist to cut maintenance costs and enhance equipment utilization but will also allow the organization to better respond to future power industry development trends, providing clients with more reliable and efficient power services [1]. Returning to the basics, the system development as indicated in Figure 1 involves connecting the electrical grid to a sensor, converting the reading from the sensor by a controller, sending the output to the gateway, and then proceeding with the advanced application. In advance applications, a graphic user interface can be created based on data collected from the IoT system to display all results across several platforms. Online data transmitted can be saved on a computer or in the cloud, which is critical for identifying failures or monitoring. More advanced applications, analytics, prediction, and forecasting can be used to determine the faults, performance, and prospective of the electrical grid. This publication elaborates on an advanced application in which IoT data will be tested using machine learning algorithms. Figure 2 shows the infrastructure that was constructed based on IoTs. The message queuing telemetry transport (MQTT) protocol was used to transfer data from the electrical facilities to the broker. Broker HiveMQ has been used based on the topic and network configuration. The data was sent via MQTT into Node-RED, and the flow design was created through a Raspberry Pi 4. The data logger was developed using the Raspberry Pi 4 and saved data for 5 seconds for each value.

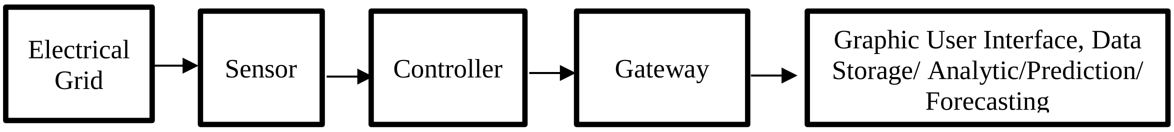

Figure 1. Basic block diagram of IoTs toward advance application

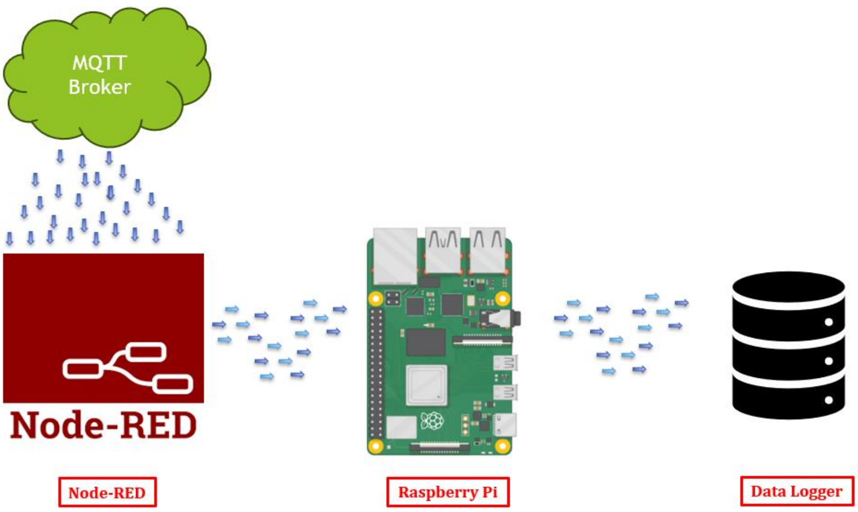

Figure 2. Infrastructure of IoTs

For the past few years, there have been a lot of research activities that try to forecast the electricity power consumption [2], [3]. The research involved not only the study of feature selection techniques, but also machine learning algorithms. Additionally, methods to select the features can be divided into three main categories, including filter, wrapper, and embedded [4]. Filter based feature selection ranks the features by calculating a score for each feature independently without depending on the learning algorithms [5]. Mutual information, Chi Square, is one of the examples of filter feature selection [6]. Wrapper method considers subsets of the set of all features. For each of the subsets, a supervised learning model is fitted. The subsets are evaluated by a performance measure calculated on the resulting model [7], such as swarm optimisation algorithms [8]. Meanwhile, the embedded technique combines the quality of both wrapper and filtering techniques, for example random forest, ridge regression, and lasso [9]. It includes the feature selection in the model fitting process [5].

On the other hand, many well known forecasting regression models were chosen, namely support vector machines (SVMs), random forest regressor, k-nearest neighbour regression (KNN), and extreme gradient boosting regression (XGBoost). SVMs have been studied a lot in the last ten years in the fields of data mining and machine learning and can be used for classification, regression, or ranking [10]. In addition, random forest is a very popular machine learning method [11]. Random forest regression is a technique that combines numerous decision trees to do regression problems [12]. Each decision tree is an inadequate learner, but when numerous decision trees are combined, random forests may create a more robust model. Random forest enhances the model's performance and generalization by constructing many decision trees and then averaging or voting on their predictions. Randomly selected subsets and random subsets of features are used to train each decision tree [12]. The KNN algorithm finds the k closest points based on the distances between the test data and the training points. It finds an average goal value in regression issues by tuning the neighbors and using weighted similarity measurements [13], [14]. XGBoost is a versatile machine learning model that lets multiple computers work together to speed up estimation and efficiently manage large datasets [14], [15].

Meanwhile, Sun *et al.* [16] laid out the essential research methods and compared the algorithms to see which algorithms were best for consumption forecasting. In addition, Junior *et al.* [17] implemented the XGBoost to forecast short-term load forecasting. The result showed that XGBoost yielded the best results. A study in [18] discusses the absence of current demand response models that consider flexible end users in relation to substation feeders. In order to dynamically analyze electric power consumption forecasts for the short term, XGBoost can be used to generate the most precise predictions of electric power consumption for distribution substations. In contrast, authors in [19] utilized an XGBoost model to forecast the daily electricity demand. Unfortunately, the study figured out that the XGBoost models had the worst prediction accuracy. In an article [20], authors discovered that the support vector regression (SVR) model provides superior reliability and accuracy in predicting short-term load compared to seven other standard forecasting methods.

Hence, based on the literature above, it is important to determine the important features that can lead towards a good performance of the forecasting models. This is because it is critical for the power distribution companies to forecast the projection of distribution system power consumptions for a proper operation and maintenance planning. As developing reliable prediction models for power consumption allows the organization to better react to changes in market demand and respond [21], failures to precisely estimate electricity use, will lead towards the overloaded transformers, influencing customer electricity consumption, and the entire power grid may fail. Therefore, this research would like to investigate the impacts of different feature selections on different machine learning models.

2. METHOD

This section will be about the process of implementing the feature selection models in selecting the most important features for predictions of the regression model. Meanwhile, Figure 3 displays the process of performing embedded and filter types of feature selections. The explanation for each of the phases will be explained on the next page.

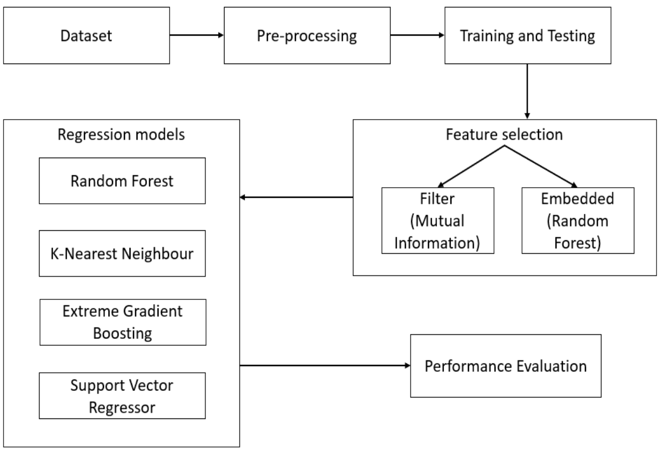

Figure 3. A framework of implementing feature selections in regression models

2.1. Dataset

The dataset used in this experiment is a private dataset consists of 500 samples with 12 features, including communities and industrial zones. The dataset was obtained from Wuzhou City, China, where the electrical grid covers an area of 12,572 square kilometers and has a population of 1.6302 million people. Descriptions for each of the features are provided on Table 1.

Table 1. Dataset description

No	Variables	Data type	Description
1	Distribution transformer name	Categorical	Name and region of distribution
2	Power supply zone	Categorical	Division of an area into sections for electricity distribution
3	Power grid type	Categorical	Type of power grid to which distribution belongs
4	Rated capacity (kVA)	Numerical	Rated power of distribution transformer
5	Distribution transformer type	Categorical	Type of distribution transformer used
6	Dry type/oil-immersed type	Categorical	Whether the distribution transformer used is dry type or oil-immersed
7	Distribution transformer model	Categorical	Model of distribution transformer
8	Load properties	Categorical	Distribution the main load object of the transformer
9	Reactive power compensation capacity (kVar)	Numerical	The capacity used to compensate for reactive power in the power system
10	Number of access users (household)	Numerical	The number of homes or units connected to the electricity service
11	Power supply radius (m)	Numerical	The area a power source can cover
12	Power supply (kWh)	Numerical	The total electrical energy provided to users in a year

2.2. Pre-processing

The dataset consists of mixed data types, including categorical and numerical values. Datatypes with categorical values must be converted to numerical values. This conversion is necessary so that they can be fitted into the machine learning models.

2.3. Training and testing

Once the dataset has been numerically converted, it is divided into a training phase and a test phase. In this phase, 70% of the dataset is used for training, while the remaining 30% is used for testing. This process is important because the performance of the model on the unseen dataset has to be measured in order to understand how the selected models will generalize towards the unseen data.

2.4. Feature selection

Then, feature selection will be performed to select the most important features. Two types of feature section methods have been chosen, which is mutual information that belongs to the filter category and random forest as an embedded type of feature selection. In order to compare the performance of the feature selection with the machine learning models later on, we decided to select the same number of features from both of the methods. Six best features were selected from both of the feature selection methods. The selected features are displayed on the result and discussion section.

2.5. Regression models

After that, the selected features will become an input for the machine learning model. Four common types of regression based machine learning models were chosen as displayed in Table 2, namely random forest regressor, KNN, XGBoost, and SVR. Meanwhile, an optimisation has been performed by using a grid search on each of the hyper-parameters of the machine learning models.

Table 2. Hyper-parameter settings after the hyper-parameter tuning process

Machine learning models	Hyper-parameters used
Random forest regressor	max_depth': None, 'min_samples_leaf': 2, 'min_samples_split': 10, 'n_estimators': 50
KNN	n_neighbors': 7, 'p': 2, 'weights': 'distance
XGBoost	colsample_bytree': 1.0, 'gamma': 0.2, 'learning_rate': 0.05, 'max_depth': 5, 'n_estimators': 50, 'subsample': 0.8
Support vector regressor	'C': 1, 'epsilon': 0.1, 'kernel': 'rbf'

2.6. Performances evaluation

After the models have been trained and tested, their performances will be measured. Three metrics were chosen, which is the mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2) [22], [23]. The MAE calculates the average absolute difference between predicted and actual values. It is derived by averaging the absolute disparities between projected and actual values for each data point. MAE is represented using the same units as the target variable. It provides a concise understanding of the model's average magnitude of mistakes. MAE is less sensitive to outliers than other error measurements, such as RMSE. The formula for MAE is based on (1).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \quad (1)$$

The RMSE calculates the square root of the average squared difference between anticipated and actual data. The squaring procedure penalizes larger errors more severely than smaller errors. RMSE is derived by calculating the square root of the average of the squared discrepancies between anticipated and actual values. The RMSE is expressed in the same units as the target variable. It indicates the typical magnitude of inaccuracy produced by the model. Due to the squaring procedure, RMSE is more susceptible to outliers than MAE is. The formula for RMSE is based on (2).

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \quad (2)$$

The coefficient of determination, often known as R^2, indicates the proportion of the variance in the dependent variable (target) that is explained by the model's independent variables (features). It goes from 0 to 1, with 0 indicating that the model does not explain any variance in the target variable and 1 indicating that the model completely explains the variance. R^2 is defined as the ratio of explained variation to total variance. Higher R^2 values imply a better match between the model and the data. The formula for R^2 is based on (3).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad (3)$$

3. RESULTS AND DISCUSSION

Figures 4 and 5 show the features that were chosen by each feature selection algorithm. The features chosen by the random forest algorithm and the mutual information are nearly identical, as seen in both figures. These features include the name of the distribution transformer, its model, its rated capacity (kVA), its reactive power compensation capacity (KVar), the number of access users (household), and its power supply radius (m). On the other hand, the distribution transformer type is the sole feature that differs among those chosen by mutual information.

```
'Distribution transformer name' 'Rated capacity(kVA)'
'Distribution transformer model'
'Reactive power compensation capacity (kVar)'
'Number of access users (household)' 'Power supply radius (m)'
```

Figure 4. Features selected by embedded based feature selection

```
['Distribution transformer name' 'Rated capacity(kVA)'
 'Distribution transformer type' 'Distribution transformer model'
 'Reactive power compensation capacity (kVar)'
 'Number of access users (household)']
```

Figure 5. Features selected by filter based feature selection

Regardless of the model being utilized, the reason for various features being selected may be related to the mutual information capability, which allows features to be directly selected depending on their direct relationship with the target variable [24]. Furthermore, when handling complex and nonlinear interactions between features and the target variable, mutual information can function effectively. In the meantime, the algorithm's hyperparameters and the unique properties of the dataset may have an impact on random forest's feature selection.

Figure 6 shows the MAE of various feature selection approaches combined with different regression algorithms. As seen in the picture, filter-based feature selection performed better with the SVR, with an MAE of 0.6028, surpassing the other three models. Following that, the random forest regressor achieved an MAE of 0.6534, the KNN regressor 0.6694, and the XGBoost regressor 0.6774. In contrast, when it comes to embedding forms of feature selection, the SVR had the best results (MAE=0.6207), while the KNN had the worst results (MAE=0.6957). As can be seen from the filter-based and embedded-based feature selection, SVR is less prone to overfitting than random forest and KNN, especially with smaller dataset sizes. Furthermore, mutual information-based feature selection is capable of capturing the non-linear relationship between features and target variables, making it a suitable option for SVR because the important features offered by mutual information are aligned with the SVR learning mechanism as the SVR also can identify the non-linear relationship between input and output [25].

The filter-based feature selection with XGBoost, on the other hand, produced the best result with 0.9566, outperforming the random forest (0.9584), SVR (0.9814), and KNN (1.0021), respectively, according to the performance of the RMSE in Figure 7. Conversely, while being tested on the XGBoost model, the features chosen by the embedded forms of feature selection obtained 0.9624. In the meantime, the KNN regressor's performance with the features chosen by the embedded feature selection types evaluated yielded the poorest result, at 1.0305. With its decision tree-based methodology, the XGBoost can capture intricate nonlinear correlations and interactions between features in this scenario. On the other hand, interactions are not explicitly modeled by KNN regressors.

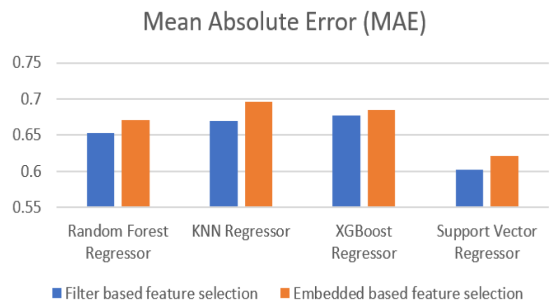

Figure 6. MAE of feature selection methods with different regression algorithms

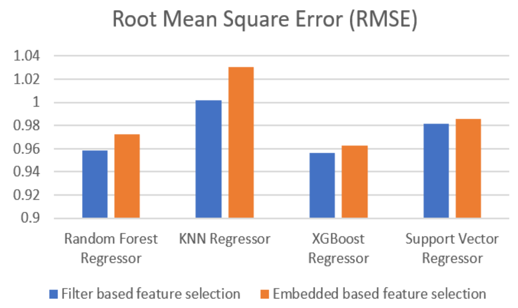

Figure 7. RMSE of feature selection methods with different regression algorithms

In contrast, the features chosen through filtering and embedded feature selection demonstrated strong performance on XGBoost, with R^2 values of 0.2561 and 0.2470, respectively as shown in Figure 8. At the same time, the KNN regressor with 0.1836 and 0.1367 became the worst model evaluated using the identical features chosen by the filter and the embedded-based feature selection. This situation arises from the ability of XGBoost, an ensemble learning technique based on decision trees, to effectively capture complex nonlinear relationships and interactions between features. It consists of the max_depth, which is able to govern tree structure, learning rate (learning_rate), regularization (gamma), and subsample. On the other hand, the KNN regressor does not explicitly describe complicated linkages or interactions; instead, it depends on the similarity of data points in the feature space.

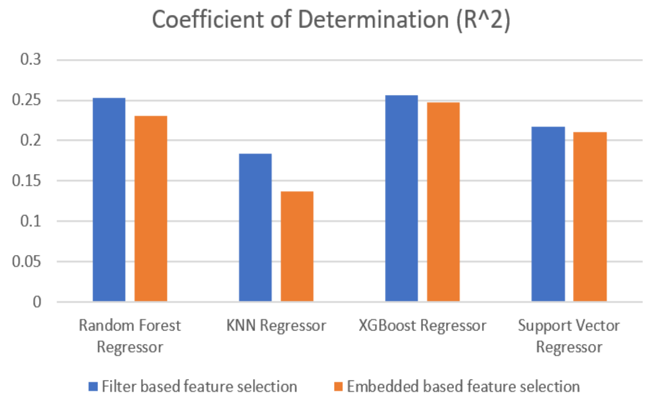

Figure 8. Coefficient of determination (R^2) of feature selection methods with different regression algorithms

4. CONCLUSION

This paper investigated various feature selection strategies for machine learning regression models in forecasting energy power usage. As can be observed from the experiment, both feature selection strategies chose nearly identical variables. However, when tested against other machine learning regression methods, mutual information, which falls into the category of filter-based feature selection, defeated embedded-based selection. Despite being tested on various machine learning techniques, both strategies produced poor results as the MAE and RMSE numbers should be zero, whereas R^2 should be one. The factors influencing the poor performance of the models resulted from insufficient data sampling, so that the regression model was unable to efficiently capture the underlying patterns in the data. In addition, a small number of features inside the data set meant that the regression model struggled with generalization. With too few features, the model may not have enough information to accurately capture the underlying patterns in the data, resulting in poor predictive performance, making the models difficult to generalize when tested on the unseen data. To solve this problem, it is necessary to increase the number of features by creating new features using feature engineering techniques.

REFERENCES

[1] G. Ziolis, J. Lopez-Lorente, M. I. Baka, A. Koumis, A. Livera, S. Theocharides, and G. E. Georghiou, "Direct short-term net load forecasting in renewable integrated microgrids using machine learning: a comparative assessment" *Sustainable Energy, Grids and Networks*, vol. 37, 2024, doi: 10.1016/j.segan.2023.101256.

[2] M. H. Widianto, A. A. S. Gunawan, Y. Heryadi and W. Budiharto, "Evaluation of machine learning on smart home data for prediction of electrical energy consumption," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*, Jakarta, Indonesia, 2023, pp. 434-439, doi: 10.1109/ICCoSITE57641.2023.10127700.

[3] W. Kim, Y. Han, K. J. Kim, and K.-W. Song, "Electricity load forecasting using advanced feature selection and optimal deep learning model for the variable refrigerant flow systems," *Energy Reports*, vol. 6, pp. 2604–2618, 2020, doi: 10.1016/j.egyr.2020.09.019.

[4] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *The Journal of Machine Learning Research*, vol. 3, pp. 1157–82, 2003, doi: 10.5555/944919.944968.

[5] A. Bommert, X. Sun, B. Bischl, J. Rahnenführer, and M. Lang, "Benchmark for filter methods for feature selection in high-dimensional classification data," *Computational Statistics & Data Analysis*, vol. 143, no. c, 2020, doi: 10.1016/j.csda.2019.106839

[6] L. Arya and G. P. Gupta, "Ensemble filter-based feature selection model for cyber attack detection in industrial internet of things," in *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, 2023, pp. 834-840, doi: 10.1109/ICACCS57279.2023.10112989.

[7] R. Kohavi and G. H. John, "Wrappers for feature subset selection," *Artificial Intelligence*, vol. 97, no. 1-2, pp. 273–324, 1997, doi: 10.1016/S0004-3702(97)00043-X.

[8] M. S. Abbasi, H. Al-Sahaf, M. Mansoori, and I. Welch, "Behavior-based ransomware classification: a particle swarm optimization wrapper-based approach for feature selection," *Applied Soft Computing*, vol. 121, 2022, doi: 10.1016/j.asoc.2022.108744.

[9] A. T. Eseye, M. Lehtonen, T. Tukia, S. Uimonen, and R. J. Millar, "Machine learning based integrated feature selection approach for improved electricity demand forecasting in decentralized energy systems," in *IEEE Access*, vol. 7, pp. 91463-91475, 2019, doi: 10.1109/ACCESS.2019.2924685.

[10] S. Maldonado and R. Weber, "A wrapper method for feature selection using support vector machines," *Information Sciences*, vol. 179, no. 13, pp. 2208-2217, 2009, doi: 10.1016/j.ins.2009.02.014.

[11] V. Jakkula, "Tutorial on support vector machine (SVM)," *School of EECS, Washington State University*, vol. 37, no. 2.5, 2006.

[12] Z. Sun, G. Wang, P. Li, H. Wang, M. Zhang, and X. Liang, "An improved random forest based on the classification accuracy and correlation measurement of decision trees," *Expert Systems with Applications: An International Journal*, vol. 237, 2024, doi: 10.1016/j.eswa.2023.121549.

[13] V. Svetnik, A. Liaw, C. Tong, J. C. Culberson, R. P. Sheridan, and B. P. Feuston, "Random forest: a classification and regression tool for compound classification and QSAR modeling," *Journal of chemical information and computer sciences*, vol. 43, no. 6, pp. 1947-1958, 2003, doi: 10.1021/ci034160g.

[14] T. Chen, and C. Guestrin, "XGBoost: a scalable tree boosting system," *arXiv*, 2016, doi: 10.48550/arXiv.1603.02754.

[15] C. H. B. Apribowo, S. P. Hadi, F. D. Wijaya, M. I. B. Setyonegoro, and Sarjiya, "Early prediction of battery degradation in grid-scale battery energy storage system using extreme gradient boosting algorithm," *Results in Engineering*, vol. 21, 2024, doi: 10.1016/j.rineng.2023.101709.

[16] Z. Sun, G. Wang, P. Li, H. Wang, M. Zhang, and X. Liang, "An improved random forest based on the classification accuracy and correlation measurement of decision trees," *Expert Systems with Applications: An International Journal*, vol. 237, 2024, doi: 10.1016/j.eswa.2023.121549.

[17] M. Y. Junior, R. Z. Freire, L. O. Seman, S. F. Stefenon, V. C. Mariani, and L. dos S. Coelho, "Optimized hybrid ensemble learning approaches applied to very short-term load forecasting," *International Journal of Electrical Power & Energy Systems*, vol. 155, 2024, doi: 10.1016/j.ijepes.2023.109579.

[18] P. Balakumar, S. K. Ramu, and T. Vinopraba, "Dynamic pricing for load shifting: reducing electric vehicle charging impacts on the grid through machine learning-based demand response," *Sustainable Cities and Society*, vol. 103, 2024, doi: 10.1016/j.scs.2024.105256.

[19] S. Ghimire, T. Nguyen-Huy, M. S. AL-Musaylh, R. C. Deo, D. Casillas-Pérez, and S. Salcedo-Sanz, "A novel approach based on integration of convolutional neural networks and echo state networks for daily electricity demand prediction," *Energy*, vol. 275, 2023, doi: 10.1016/j.energy.2023.127430.

[20] Y. Chen *et al.*, "Short-term electrical load forecasting using the support vector regression (SVR) model to calculate the demand response baseline for office buildings," *Applied Energy,* vol. 195, pp. 659-670, 2017, doi: 10.1016/j.apenergy.2017.03.034.

[21] C. V. Zyl, X. Ye, and R. Naidoo, “Harnessing explainable artificial intelligence for feature selection in time series energy forecasting: a comparative analysis of Grad-CAM and SHAP,” *Applied Energy*, vol. 353, 2024, doi: 10.1016/j.apenergy.2023.122079.

[22] G.-F. Fan, X. Wei, Y.-T. Li, and W.-C. Hong, “Forecasting electricity consumption using a novel hybrid model,” *Sustainable Cities and Society*, vol. 61, 2020, doi: 10.1016/j.scs.2020.102320.

[23] C. Liu, B. Sun, C. Zhang, and F. Li, “A hybrid prediction model for residential electricity consumption using holt-winters and extreme learning machine,” *Applied Energy*, vol. 275, 2020, doi: 10.1016/j.apenergy.2020.115383.

[24] H. Zhou, X. Wang, and R. Zhu, “Feature selection based on mutual information with correlation coefficient,” *Applied Intelligence*, vol. 52, no. 5, pp. 5457–5474, 2022, doi: 10.1007/s10489-021-02524-x.

[25] M. S. Alam, N. Sultana, and S. M. Z. Hossain, “Bayesian optimization algorithm based support vector regression analysis for estimation of shear capacity of FRP reinforced concrete members,” *Applied Soft Computing*, vol. 105, 2021, doi: 10.1016/j.asoc.2021.107281.

BIOGRAPHIES OF AUTHORS

Azman Ab Malik received his diploma in electronic technology from Kolej Kemahiran Tinggi MARA (KKTM) Pasir Mas in 2007, bachelor in electrical engineering and technology from Universiti Kuala Lumpur British Malaysian Institute (UNIKL BMI), master in electrical and electronic engineering from Universiti Sains Malaysia (USM) and Ph.D. in electrical engineering from Universiti Teknologi MARA (UITM). His interest in innovation towards electrical and electronic and cross multi-disciplinary areas to identify a new model or method in engineering. His research interests included electrical power, power system, renewable energy, and energy storage. He is currently a senior lecturer in School of Computer Science, Universiti Sains Malaysia. He can be contacted at email: azman.abdul@usm.my.

Lyu Tao received his bachelor of electronics and information engineering from Shanghai Electric Power University in 2021. Currently, he is pursuing a master's degree in master of science (data science and analytics) from Universiti Sains Malaysia. His research interests include big data research and analysis, and machine learning. He can be contacted at email: lyutaolt@student.usm.my.

Noormadinah Allias received her bachelor of engineering technology (Hons) in networking systems from University Kuala Lumpur - Malaysian Institute of Information Technology (UniKL - MIIT) in 2008. She obtained her master and Ph.D. of information technology from the same institution (UniKL- MIIT) in 2015 and 2024 respectively. Currently, she serves as a senior lecturer at School of Computing Sciences, College of Computing, Informatics and Mathematics, Universiti Teknologi MARA, Shah Alam, Malaysia. Her research interests include next generation network, cybersecurity, data analytics, and machine learning. She can be contacted at email: noormadinah@tmsk.uitm.edu.my.

Irni Hamiza Hamzah was born in Machang, Kelantan on 6th December 1974. She obtained her B.Eng. (Hons) in electrical and electronic engineering in 1998, M.Sc. electronics system and design engineering in 2005 and Ph.D. in BioMEMs sensors in 2013, which all had been obtained from School of of Electrical and Electronic Engineering, Universiti Sains Malaysia, Malaysia. She is currently a senior lecturer in Department of Electronic Engineering, Faculty of Electrical Engineering, Universiti Teknologi MARA, Penang Branch Campus, Malaysia. Her research interests include biosensors, BioMEMs, neural networks, and renewable energy. She can be contacted at email: irnihami@uitm.edu.my.