International Journal of Advances in Applied Sciences (IJAAS)
Vol. 14, No. 2, June 2025, pp. 310~321
ISSN: 2252-8814, DOI: 10.11591/ijaas.v14.i2.pp310-321

Enhancing artificial neural network performance for energy efficiency in laboratories through principal component analysis

Desmira[1,2], Norazhar Abu Bakar[3], Mustofa Abi Hamid[1,2,4], Muhammad Hakiki[5], Affero Ismail[6,7], Radinal Fadli[2,4,8]
[1]Department of Electrical Engineering Vocational Education, Universitas Sultan Ageng Tirtayasa, Serang, Indonesia
[2]Center for Vocational and Technical Education and Training (Voctech), Yogyakarta, Indonesia
[3]Department of Electrical and Electronics Engineering, Universiti Teknologi Petronas, Seri Iskandar, Malaysia
[4]Department of Technological and Vocational Education, Graduate School, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[5]Department of Information Technology Education, Universitas Negeri Surabaya, Surabaya, Indonesia
[6]Department of Engineering Education, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Malaysia
[7]UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, Bonn, Germany
[8]Department of Information Technology Education, Universitas Lampung, Bandar Lampung, Indonesia

Article Info

Article history:

Received Oct 18, 2024
Revised Feb 22, 2025
Accepted Mar 28, 2025

Keywords:

Artificial neural network
Energy efficiency
Enhancing performance
Forecast energy
Principal component analysis

ABSTRACT

This study investigates energy efficiency challenges during laboratory activities. Inefficient energy use in the practicum phase remains a critical issue, prompting the exploration of innovative forecasting models. This research employs artificial neural network (ANN) models integrated with principal component analysis (PCA) to predict energy consumption and optimize usage. The findings reveal that PCA components, including eigenvalues, eigenvectors, and matrix covariance values, significantly influence the ANN model's performance in forecasting energy production. The ANN training achieved a high correlation coefficient (R=1) with a mean squared error (MSE) of 0.045931 after 200,000 epochs, demonstrating the model's robustness. While testing results showed a moderate correlation (R=0.46169), the models demonstrated potential for refinement and scalability. This integration of ANN and PCA models provides a reliable framework for accurately forecasting energy usage, offering an effective strategy to enhance energy efficiency in laboratory settings. By optimizing energy consumption, this approach has the potential to reduce operational costs and environmental impact. The strong performance metrics highlight the practical utility of these models in educational contexts, contributing to sustainable energy management and better resource allocation. Furthermore, the reduction in energy-related environmental impacts underscores the broader applicability of these models for fostering sustainable development in similar contexts.

Corresponding Author:

Muhammad Hakiki
Department of Information Technology Education, Universitas Negeri Surabaya
Jl. Ketintang Wiyata Gedung A10, Ketintang, Gayungan, Surabaya, East Java 60231, Indonesia
Email: muhammadhakiki@unesa.ac.id

1. INTRODUCTION

According to International Energy Agency (IEA) predictions for the period 2006-2030, the majority of global energy demand, accounting for 87%, is derived from non-Organization for Economic Co-operation and Development (OECD) nations [1], [2]. China is expected to experience the highest rise in energy demand compared to other areas [3]–[12]. India has recently experienced a significant increase in energy consumption, which is one rung lower than that of China [13]–[23]. In Indonesia, there have been multiple initiatives aimed at conserving indoor energy use. Additionally, the university has also implemented numerous measures to achieve efficient and consistent energy usage. The utilization of energy in order to attain energy efficiency necessitates the implementation of a smart room equipped with diverse input sensors that impact indoor energy usage [24], [25]. Energy consumption refers to the quantity of energy that a building needs to provide at any particular moment. The overconsumption of electrical energy has the potential to exacerbate energy wastage and have adverse effects on the environment [26], [27]. The anticipation of building energy consumption is a significant methodology in the realm of energy conservation, yielding advantages for both individuals and society by facilitating more prudent construction of new structures. Accurate forecasting of energy usage in buildings is crucial for enhancing energy efficiency, to attain energy conservation, and minimize ecological consequences [28]–[32].

The mismanagement of energy use has the potential to negatively affect the efficiency of energy usage, resulting in the wastage of power [33]. The present study aimed to construct a prediction model for energy consumption in the Laboratory of Electrical and Power Engineering (LEPE) at Universitas Sultan Ageng Tirtayasa. The environment has a considerable impact on energy consumption in colleges [34], [35]. Guang Dong University has done research that demonstrates the substantial energy savings achieved via the development of a conservation-oriented campus. Measuring indices of energy use has shown to be challenging in this study [36], [37]. University buildings in China implement specific energy efficiency measures tailored to local requirements, taking into account elements such as the presence of several campuses and climate conditions, which pose challenges in achieving energy efficiency in the buildings [38]. Efficient energy consumption in a building was achieved by aggregating historical data on daily electricity use in two buildings. This aggregation was performed using normalized data from six input variables [39]. The analysis of three campus buildings in Tianjin indicates that the average electricity usage per inhabitant fluctuates based on the building's purpose and the method of controlling electrical equipment [40]. Statistical regression methods are employed to comprehend the correlation between individual variables and energy consumption [41]. Previous research methods have demonstrated the applicability of enhanced modeling in other types of buildings, provided that it incorporates an energy consumption monitoring platform, rather than being restricted to campus buildings [42].

The behavior of room users is one of the input characteristics in a building that influences energy use; this behavior has a significant impact on how the space is used and complicates the calculation of the required energy consumption [43]. While features are directly used as input in the prediction step of earlier energy consumption prediction models [44]–[49], in this study, feature selection was done prior to the prediction stage. The goal of feature selection is to identify a few characteristics that have the biggest impact on energy usage [50]. It is anticipated that the selection of features will lead to a more accurate and efficient prediction stage. The aim of the feature selection approach is to reduce the set by eliminating certain features that are deemed unnecessary for text sentiment classification. This will enhance classification accuracy and shorten the training time of machine learning models [51]. To get a trustworthy transformation, attribute selection has the drawback of requiring training on a big data set [52]. Feature selection is one method for getting around the excessive dimensions of features. Reducing vector dimensions has been accomplished by using information gain [53], one of the feature selection methods [54].

Dimension reduction is an additional strategy that can be employed to address the issue of high feature dimensions, alongside feature selection techniques. The dimension reduction technique aims to acquire novel data representations that are effectively reduced in size [55]. The dimensional reduction linear model comprises the singular value decomposition (SVD) model and the PCA model [56]. Nevertheless, the linear model of dimensional reduction has a drawback in that it generates a linear combination of all features, which can be influenced by noise and diminish the performance of the classification model. Additionally, the linear model of dimensional reduction encounters challenges when dealing with non-linear data [57]. The present study employed the PCA model for feature selection, and the artificial neural network (ANN) model for the prediction stage. The data utilized for energy consumption prediction encompassed various parameters, namely temperature sensor DHT22, temperature sensor BMP180, pressure, humidity, voltage, current, power, altitude, and light intensity. Concurrently, the prediction model produces energy consumption as its output.

2. METHOD

Figure 1 depicts the flowchart of an energy consumption prediction model that employs PCA as a feature selection technique. Based on the analysis of historical data utilized as inputs for PCA models, it is evident that the input variables initially comprised 9 sensors. However, in order to streamline the data and enhance its display efficiency, the ANN model was employed, resulting in a reduced set of 4 input variables. Additionally, the PCA model serves the function of transforming the initially correlated data into uncorrelated data. Consequently, the data will be more visually presented and the subsequent stage of the ANN model will be completed more quickly [29]. The initial step in getting the covariance matrix needed to calculate the values of eigenvectors and eigenvalues in PCA is normalization [58]. The assignment of eigenvectors and eigenvalues can provide insight into the extent to which input variables influence PC variables.

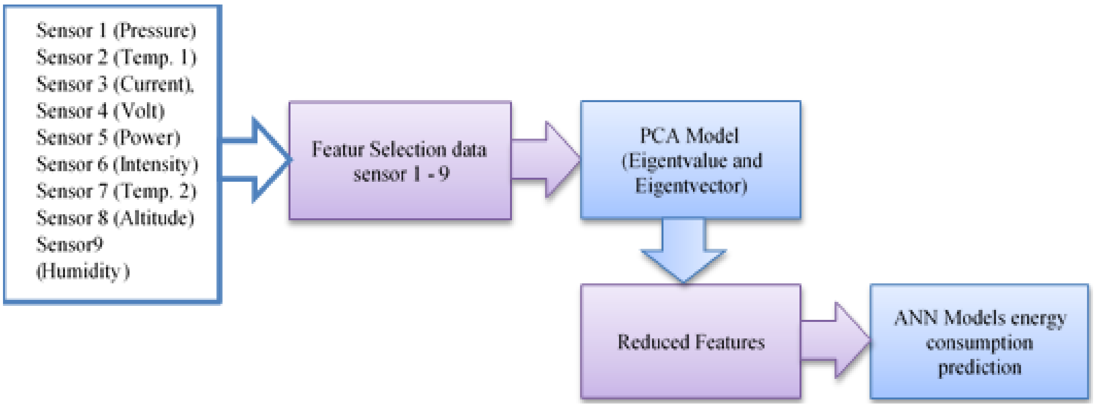


Figure 1. Flowchart of the PCA and ANN-based method for energy consumption prediction

According to the data presented in Figure 1, it is evident that the data collected is real-time data obtained from the LEPE. The design employs a total of 9 sensors that are interconnected with the device utilized for data retrieval. Sensor 1 comprises data pertaining to pressure, whereas sensor 2 and sensor 7 encompass data pertaining to temperature. Sensor 3 is associated with the data pertaining to the electrical current within the circuit. Sensor 4 is a voltage-connected data sensor. The data retrieval of sensor 8 pertains to the altitude distance, as it is directly associated with the forecast of energy consumption.

2.1. Feature selection using principal component analysis

The study employed PCA to enhance computation precision and decrease training time [59]. PCA was employed to reduce and transform the data utilized in this study. This involved excluding irrelevant data throughout the PCA process, computing the covariance matrix of the data, and identifying eigenvectors and eigenvalues. The process began with calculating the covariance matrix to capture the relationships and variance among all features in the dataset. Eigenvectors and eigenvalues were subsequently derived to identify the principal components that account for maximum variance within the data. These principal components were then utilized to transform the original dataset into a reduced feature space while preserving its most critical informational content. This methodological approach enhanced computational efficiency by reducing the overall feature set and mitigated the risk of overfitting, thereby improving the model's generalizability. The process of selecting features using the PCA approach involves the following steps:

i) The computation of the covariance matrix involves the subtraction of the mean value of feature data characteristics.
ii) The eigenvectors and eigenvalues of the covariance matrix are computed. The process involves selecting m-number eigenvalues from the list of eigenvectors and subsequently assigning these eigenvectors as $v_1, \dots, v_m$.
iii) Calculating the contribution of each feature with the (1).

$$c_j = \sum_{p=1}^{m} |v_{pj}| \tag{1}$$

iv) Choosing the largest number of c_j values according to the number of features you want to maintain, so you get the jth feature which is a significant feature.

Several carefully selected features, derived from the preprocessing and dimensionality reduction stages, were subsequently utilized as input variables for the energy consumption prediction phase. This step aimed to ensure that the most relevant and significant features contributed to the predictive modeling process, thereby enhancing the accuracy and reliability of the results. Two distinct predictive algorithms were utilized for this purpose, including the ANN algorithm, a recognized method noted for its strong ability to model complex nonlinear relationships. The study utilized these algorithms to produce accurate and dependable predictions of energy consumption, highlighting the effectiveness of feature selection and algorithmic adaptability in tackling complex forecasting issues.

2.2. Energy consumption prediction using artificial neural network and principal component analysis algorithms

Pressure, temperature sensor DHT22, current, voltage, power, light intensity, temperature sensor BMP180, altitude, and humidity all influence the estimation of electrical energy requirements in the LEPE. The laboratory collected an average of 67 days of data using a single layer of hidden network in order to reduce the computational time required for prediction using ANN [60]. The ANN technique is used as a computational tool using a feedforward network type to estimate the energy consumption of the two laboratories at the Faculty of Electrical Engineering (FKE), Universiti Teknologi MARA (UiTM) Malaysia. The results indicate that the ANN is effectively trained to forecast energy usage [33]. A study conducted by [61], indicates that both the improved particle swarm optimization (iPSO)-ANN and a hybrid genetic algorithm (GA)-ANN surpass the conventional ANN in terms of prediction accuracy. Additionally, the improved particle swarm optimization (iPSO)-ANN model most significantly reduces computational time, establishing it as a feasible choice for real-time energy forecasting. Boujoudar *et al.* [62] is currently engaged in the integration of ANN to estimate the state of charge (SOC) of batteries and to manage bidirectional converters. The performance and robustness of the suggested control strategy are elucidated by the simulation results obtained in the MATLAB/Simulink environment. In order to enhance the efficacy of the ANN in forecasting the demand for electrical energy within a laboratory setting, it is imperative to consider the impact of eigenvectors and eigenvalues of the principal component of each input variable on the reduction and transformation processes.

2.3. Artificial neural network and principal component analysis prediction performance test

To assess and evaluate the precision of data collected in real-time in the LEPE, one can compare the actual data or original data using the ANN approach. The mean square error (MSE) formula was employed to compare actual measurement data with predicted data generated by the ANN model. The MSE is employed to assess the precision of forecasting outcomes in relation to the initial dataset of laboratory measurements. The range of forecasting results and MSE values is from 0 to infinity, with 0 representing the optimal value [63]. The MSE can be computed using the (2).

$$MSE = \frac{\sum_{i=1}^{n}(yi-\bar{y})^2}{n} \tag{2}$$

3. RESULTS AND DISCUSSION

The present study employed the PCA model for feature selection, and the ANN model for the prediction stage. The data utilized for energy consumption prediction encompassed various parameters, namely temperature sensor DHT22, temperature sensor BMP180, pressure, humidity, voltage, current, power, altitude, and light intensity. Concurrently, the prediction model produces energy consumption as its output. The network was trained using MATLAB 2019a. The algorithms underwent testing in order to ascertain the most optimal algorithm for application. The Levenberg-Marquardt method [64]–[66] was evaluated for its ability to create output in accordance with the intended iteration target. The algorithm was found to be the fastest in terms of training results and testing correlation coefficient R=1, indicating that the average error in the training data from each test is close to zero. The binary sigmoid and identity activation functions were selected based on the highest performance in all experiments. When the iteration objective is met, the training on data is terminated after 1,000 iterations, with an epoch of 200,000. The training data utilized variable input derived from sensor data, which underwent feature selection using the PCA model. Table 1 demonstrates that the eigenvector and eigenvalue aligned with (1) following the grouping of the data and the acquisition of PCA results presented in Table 1.

The data in Table 1 indicates that the dimension reduction process, particularly the selection of principal components (PC1 to PC9), yields eigenvectors and eigenvalues that outperform those chosen for the ANN model. Table 1 shows that the eigenvalues for PC1 to PC4 surpass the threshold value of 1, indicating that these components significantly contribute to the variance in the dataset. This finding underscores the efficacy of the PCA method in isolating the most informative components while minimizing noise and redundancy. In the next phase, the values corresponding to PC1 and PC4, recognized as the most significant principal components, will be utilized as inputs for the ANN model [67]–[69]. This selection seeks to utilize the essential features for forecasting energy consumption in the LEPE.

Table 1. The performance of PCA transformation results

No	Principle component analysis (PCA)	Reduction PCA = $c_j = \sum_{p=1}^{m} \lvert v_{pj} \rvert$
1	PCA 1	3.2
2	PCA 2	1.7
3	PCA 3	1.5
4	PCA 4	1.1
5	PCA 5	0.7
6	PCA 6	0.5
7	PCA 7	0.2
8	PCA 8	0.05
9	PCA 9	0.03

$$var(Pressure\ (atm)) = \frac{\sum_{i=1}^{n}(x_1 - \overline{x})}{n=1} \quad (3)$$

$$var(Temp\ ℃) = \frac{\sum_{i=1}^{n}(y_1 - \overline{y})}{n=1} \quad (4)$$

Variants of each data were obtained using (2) and (3) to determine eigenvectors and eigenvalues. In epoch 1,000, the MSE training [70] achieved a value of 0.045931. The test yielded a correlation coefficient R=0.35136, with 9 input variables and one output. The ANN structure employed the gaussmf input membership function. Figure 2 displays a dataset consisting of 50 training data points, which resulted in a correlation coefficient of R=1 after 2,000 epochs. Figures 2(a) and 2(b) show PCA and ANN data training with R=1 and dataset index, while Figure 2(c) displays the best training performance. Gradient, validation check, and learning rate can be seen in Figure 2(d) and the training state plot in Figure 2(e).

Figure 2 demonstrates that the ANN model achieves a high level of accuracy in both the distribution of real data and predicted data. The correlation coefficient R is 1, and the MSE is 0.045931, indicating that the model has met its aim after 1,000 iterations. A learning rate of 2.3732e-05 was observed. The duration required to reach the designated objective was 6.29 minutes. In each epoch, the gradient value was recorded as 2.0265, the validation check was set to 0, and the learning rate was maintained at 2.3732e-05.

Similar to the data training phase, the testing phase employed ANN [59], [61], [68], [71] set with both binary and identity sigmoid activation functions to guarantee the best performance in modeling nonlinear interactions within the data. This phase sought to confirm the model's generalizability and its capacity to reliably forecast energy consumption using previously unexamined test data. The testing procedure produced an MSE score of 0.045931, signifying little error and high predicted accuracy. Figure 3 presents a comprehensive comparison between the anticipated energy values from the ANN model and the actual energy usage data. This image underscores the model's capacity to accurately replicate real-world energy computations, demonstrating its durability and the efficacy of the ANN design in identifying the fundamental patterns within the data. The correlation between training and testing results highlights the dependability and relevance of the ANN model in real-world energy forecasting contexts.

The comparison of actual energy data with testing data using ANN and PCA models in the LEPE, as depicted in Table 2 and Figure 3, demonstrates a comparable level of resemblance. The ANN+PCA model accurately predicts the real energy use in the LEPE for training data ranging from 1 to 50. A disparity was seen in the 41st dataset, where the measured energy was 192.017959 Wh, however, the energy measurement obtained by the utilization of the ANN+PCA model was 191.9991 Wh. The test utilized an actual energy difference of 348.7287 Wh for the 50th data, whereas the ANN+PCA model utilized 235.3984 Wh. Figure 4 shows testing prediction energy (actual) vs. ANN+PCA, specifically Figure 4(a) shows the testing and output data, and Figure 4(b) shows the testing dataset index.

A total of 17 and 50 training data sets were carefully chosen for the testing phase to guarantee a broad representation of the dataset. The selection of test data conformed to the criteria outlined in Table 3, guaranteeing consistency and alignment with the experimental design. The test results, shown in Figure 5, demonstrate significant differences between the anticipated test data points and the actual target test data points when using the ANN model. The scatter plot clearly illustrates this discrepancy, showing that the model's predictions diverge markedly from the target values. The test produced a correlation coefficient (R) of 0.46169, indicating a reasonable but inadequate connection between the anticipated and actual results. This outcome highlights the difficulties encountered by the ANN model in precisely representing the connections within the test dataset, which may be attributable to constraints in model complexity, data unpredictability, or the need for further optimization of input features and hyperparameters. Additional study and enhancement of the ANN model may be necessary to augment its predicted accuracy and resilience.

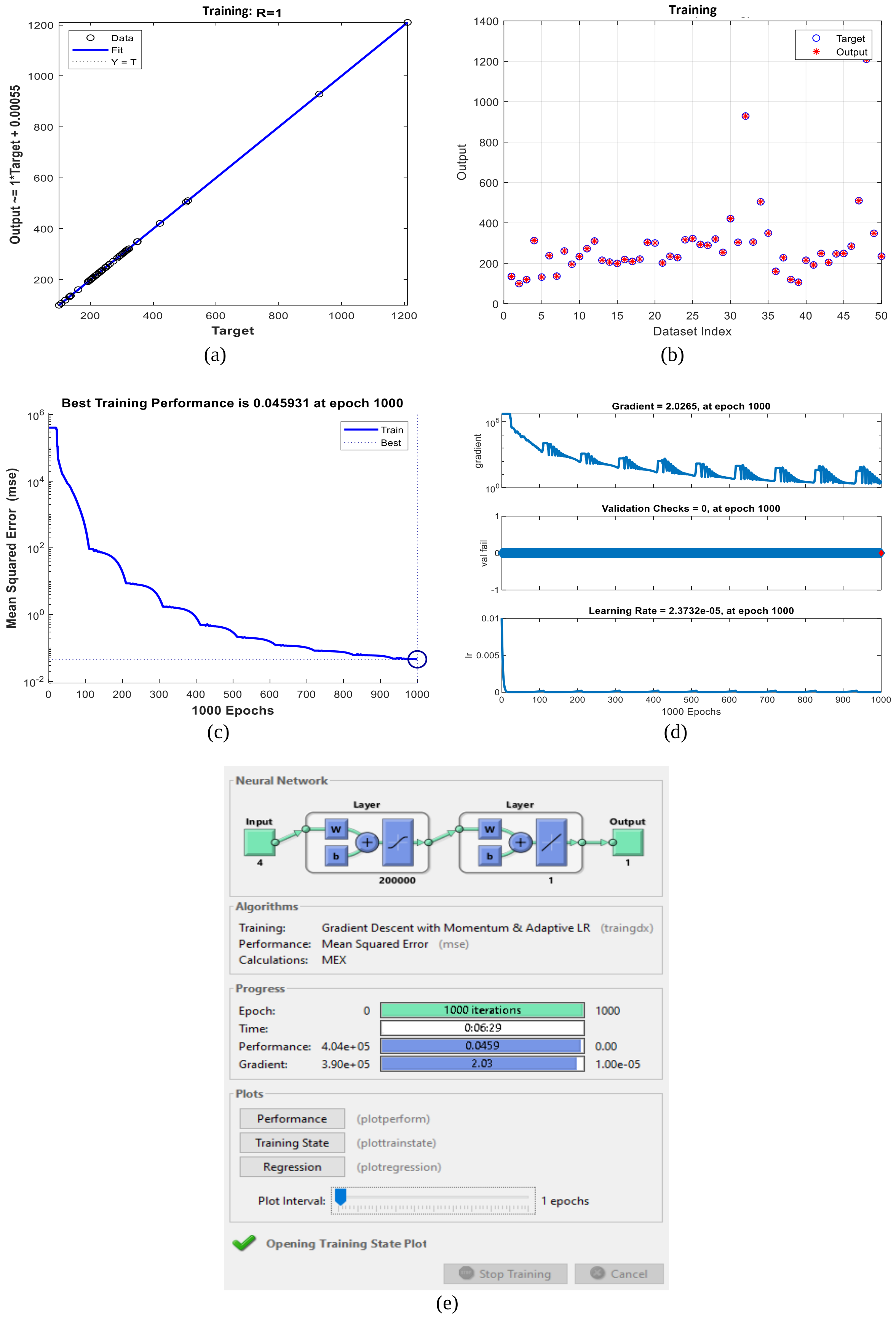


Figure 2. PCA and ANN data training of (a) training R=1, (b) output and target, (c) best training performance, (d) gradient, validation check, and learning rate, and (e) training state plot

Table 2. Training data

No	Day/Date	Pressure (atm)	Energy (actual) (Wh)	Prediction ANN+PCA (Wh)
1	Mon, 6-1-20	0.9928	135.111837	135.1109
2	Tue, 7-1-20	0.992116327	99.6604082	99.6609
3	Wed, 8-1-20	0.991714286	119.275102	119.2747
4	Thu, 9-1-20	0.992320408	312.561633	313.6165
5	Fri,10-1-20	0.991587755	132.153469	132.1516
6	Mon, 13-1-20	0.991695918	237.80898	237.8186
7	Tue,14-1-20	0.992167347	138.8847	136.7702
8	Wed, 15-1-20	0.99155102	261.102041	261.0997
9	Thu, 16-1-20	0.990463265	195.777959	195.7711
10	Fri, 17-1-20	0.991891837	233.271837	233.2715
….	….	….	….	….
….	….	….	….	….
50	Wed, 18-3-20	0.992332653	349.33551	235.3984

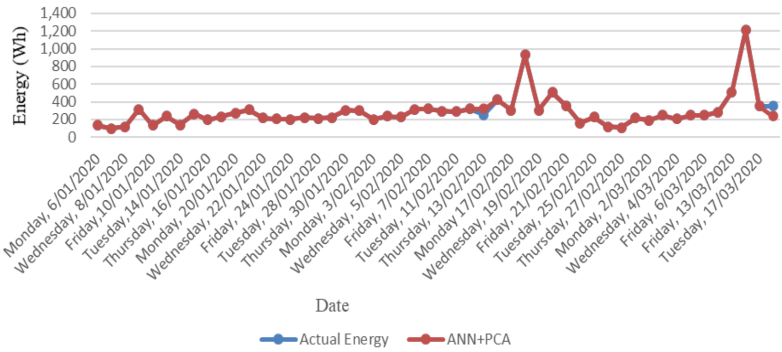
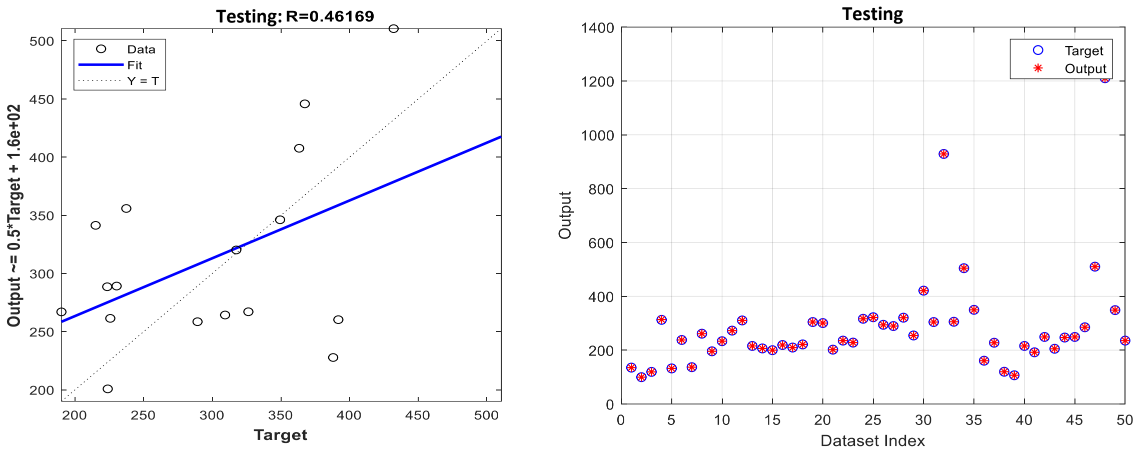


Figure 3. Training prediction energy (actual) vs. ANN+PCA



(a) (b)

Figure 4. Testing prediction energy (actual) vs. ANN+PCA of (a) testing and output and (b) testing dataset index

Table 3. ANN+PCA testing

No	Day, Date	Pressure (atm)	Energy (actual) (Wh)	Prediction ANN+PCA (Wh)
1	Mon, 6-1-20	0.9928	135.111837	135.1109
2	Tue, 7-1-20	0.992116327	99.6604082	99.6609
3	Wed, 8-1-20	0.991714286	119.275102	119.2747
4	Thu, 9-1-20	0.992320408	312.561633	313.6165
5	Fri,10-1-20	0.991587755	132.153469	132.1516
6	Mon, 13-1-20	0.991695918	237.80898	237.8186
7	Tue,14-1-20	0.992167347	138.8847	136.7702
8	Wed, 15-1-20	0.99155102	261.102041	261.0997
….	….	….	….	….
67	Fri, 10-4-20	0.993185714	391.766531	260.263

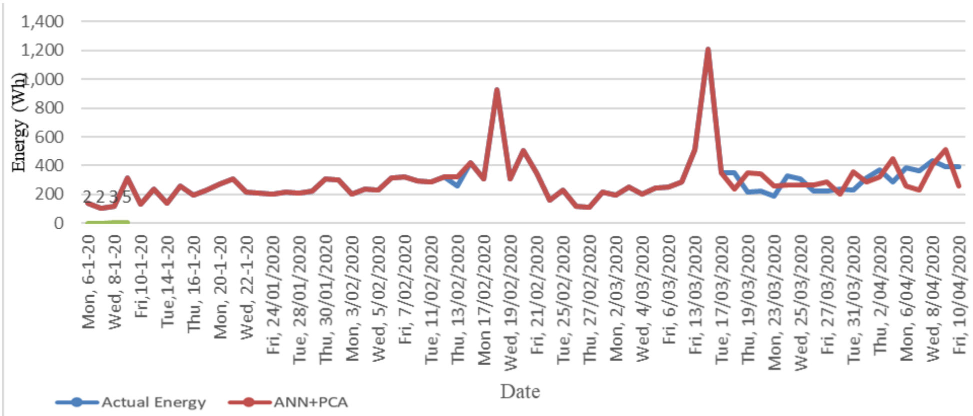


Figure 5. Prediction energy actual vs. ANN+PCA

From Figure 5, it can be seen that the difference between actual energy data and data from ANN+PCA indicates a considerable difference in 17 test data against the output target based on conventional calculations. For training data from 1 to 50, the predictions of actual energy usage in the LEPE were almost the same as prediction data with ANN+PCA models. Meanwhile, the test data from data 51 to 67 showed that the data changes were quite significant in test data 62, which resulted in -156.541002 Wh, and significant in test data 65, which showed 24.47521633 Wh.

4. CONCLUSION

Based on the findings of the research conducted at the LEPE, the comparison between the real data and the predicted data using the ANN model, with feature selection employing PCA, yielded highly favorable results. The correlation coefficient during training was R=1, however, during testing, the correlation coefficient was R=0.4883 with an MSE of 0.045931 in epoch 1,000. Based on the findings of a three-month research study, it was observed that the actual data and traditional calculation data closely aligned with the data generated through the application of the ANN model using PCA feature selection. Hence, the ANN model, employing PCA for feature selection, is highly effective in forecasting energy requirements in a laboratory setting, while also considering the comfort of students during their practicum in the room.

ACKNOWLEDGEMENTS

We express our gratitude to the Universitas Sultan Ageng Tirtayasa for granting us permission to carry out our research at their laboratory. We would also like to extend my appreciation to all the supervisors at Universiti Teknikal Malaysia Melaka.

FUNDING INFORMATION

The authors state no funding is involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Desmira	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Norazhar Abu Bakar	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Mustofa Abi Hamid		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓
Muhammad Hakiki		✓	✓		✓			✓		✓	✓			
Affero Ismail		✓			✓					✓				
Radinal Fadli		✓			✓					✓				

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author [D and NAB], upon reasonable request.

REFERENCES

[1] J. Rutovitz and A. Atherton, "Energy sector jobs to 2030 : a global analysis," Sydney, 2009.
[2] J. Iwaro and A. Mwasha, "A review of building energy regulation and policy for energy conservation in developing countries," *Energy Policy*, vol. 38, no. 12, pp. 7744–7755, 2010, doi: 10.1016/j.enpol.2010.08.027.
[3] X. C. Yuan, X. Sun, W. Zhao, Z. Mi, B. Wang, and Y. M. Wei, "Forecasting China's regional energy demand by 2030: a Bayesian approach," *Resources, Conservation and Recycling*, vol. 127, no. May, pp. 85–95, 2017, doi: 10.1016/j.resconrec.2017.08.016.
[4] J. Eom, L. Clarke, S. H. Kim, P. Kyle, and P. Patel, "China's building energy demand: long-term implications from a detailed assessment," *Energy*, vol. 46, no. 1, pp. 405–419, 2012, doi: 10.1016/j.energy.2012.08.009.
[5] T. Ito, Y. Chen, S. Ito, and K. Yamaguchi, "Prospect of the upper limit of the energy demand in China from regional aspects," *Energy*, vol. 35, no. 12, pp. 5320–5327, Dec. 2010, doi: 10.1016/J.ENERGY.2010.07.028.
[6] Z. Jiang and B. Lin, "China's energy demand and its characteristics in the industrialization and urbanization process," *Energy Policy*, vol. 49, pp. 608–615, Oct. 2012, doi: 10.1016/J.ENPOL.2012.07.002.
[7] Y. Fan and Y. Xia, "Exploring energy consumption and demand in China," *Energy*, vol. 40, no. 1, pp. 23–30, Apr. 2012, doi: 10.1016/J.ENERGY.2011.09.049.
[8] S. Wei Yu and K. Jun Zhu, "A hybrid procedure for energy demand forecasting in China," *Energy*, vol. 37, no. 1, pp. 396–404, Jan. 2012, doi: 10.1016/J.ENERGY.2011.11.015.
[9] B. Lin and X. Ouyang, "Energy demand in China: comparison of characteristics between the US and China in rapid urbanization stage," *Energy Conversion and Management*, vol. 79, pp. 128–139, Mar. 2014, doi: 10.1016/J.ENCONMAN.2013.12.016.
[10] L. Liu, J. Huang, and S. W. Yu, "Prediction of primary energy demand in China based on agaede optimal model," *Chinese Journal of Population Resources and Environment*, vol. 14, no. 1, pp. 16–29, Jan. 2016, doi: 10.1080/10042857.2015.1111572.
[11] F. Cheng, S. Yang, and K. Zhou, "Quantile partial adjustment model with application to predicting energy demand in China," *Energy*, vol. 191, Jan. 2020, doi: 10.1016/j.energy.2019.116519.
[12] C. Rao, Y. Zhang, J. Wen, X. Xiao, and M. Goh, "Energy demand forecasting in China: a support vector regression-compositional data second exponential smoothing model," *Energy*, vol. 263, Jan. 2023, doi: 10.1016/j.energy.2022.125955.
[13] R. Manickam and S. N. Palaniappan, "Upgrading transmission line capability by AC–DC conversion," *Computers & Electrical Engineering*, vol. 68, pp. 616–628, May 2018, doi: 10.1016/J.COMPELECENG.2018.01.031.
[14] T. Ekholm, V. Krey, S. Pachauri, and K. Riahi, "Determinants of household energy consumption in India," *Energy Policy*, vol. 38, no. 10, pp. 5696–5707, Oct. 2010, doi: 10.1016/J.ENPOL.2010.05.017.
[15] M. Vijayan, A. Patil, and V. Kapse, "An agent-based computational model on household electricity consumption in Indian cities," *Journal of Green Building*, vol. 19, no. 1, pp. 235–260, Feb. 2024, doi: 10.3992/jgb.19.1.235.
[16] U. Kumar and V. K. Jain, "Time series models (grey-markov, grey model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India," *Energy*, vol. 35, no. 4, pp. 1709–1716, Apr. 2010, doi: 10.1016/J.ENERGY.2009.12.021.
[17] C. F. Tang, A. K. Tiwari, and M. Shahbaz, "Dynamic inter-relationships among tourism, economic growth and energy consumption in India," *Geosystem Engineering*, vol. 19, no. 4, pp. 158–169, Jul. 2016, doi: 10.1080/12269328.2016.1162113.
[18] V. Akram, B. P. Jangam, and B. N. Rath, "Does human capital matter for reduction in energy consumption in India?," *International Journal of Energy Sector Management*, vol. 13, no. 2, pp. 359–376, May 2019, doi: 10.1108/IJESM-07-2018-0009/FULL/PDF.
[19] M. Naimoglu, İ. Kavaz, and A. I. Simsek, "Effects of foreign direct investment, economic integration, industrialization and economic growth on energy intensity: case of India," *Asia-Pacific Journal of Regional Science*, vol. 8, no. 1, pp. 333–354, Mar. 2024, doi: 10.1007/S41685-024-00329-7/METRICS.
[20] P. Kumar, S. Gupta, and V. Dagar, "Sustainable energy development through non-residential rooftop solar photovoltaic adoption: empirical evidence from India," *Sustainable Development*, vol. 32, no. 1, pp. 795–814, Feb. 2024, doi: 10.1002/SD.2644.
[21] X. Qi, L. Ju, S. Yang, W. Gan, G. Li, and X. Bai, "A bi-level peer-to-peer interactive trading optimization model and distributed solution algorithm for rural distributed energy system group based on Stackelberg-Nash game strategy," *Energy*, vol. 318, no. 1, p. 134767, 2025, doi: 10.1016/j.energy.2025.134767.
[22] S. Khanna and K. Rowe, "The long-run value of electricity reliability in India," *Resource and Energy Economics*, vol. 77, Apr. 2024, doi: 10.1016/j.reseneeco.2024.101425.
[23] R. Sharma, S. Goel, S. R. Lenka, and P. R. Satpathy, "Energy efficiency retrofitting measures of an institutional building: a case study in eastern India," *Cleaner Energy Systems*, vol. 7, Apr. 2024, doi: 10.1016/j.cles.2024.100111.
[24] M. V. Moreno, B. Úbeda, A. F. Skarmeta, and M. A. Zamora, "How can we tackle energy efficiency in IoT based smart buildings?," *Sensors*, vol. 14, no. 6, pp. 9582–9614, 2014, doi: 10.3390/s140609582.
[25] I. A. Darmawan *et al.*, "Electricity course on vocational training centers: a contribution to unemployment management," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, Feb. 2020. doi: 10.1088/1742-6596/1456/1/012048.

[26] A. Rahmat, A. R. Nugroho, A. Saregar, M. A. Hamid, M. R. N. Prastyo, and A. Mutolib, "Small hydropower potential of rivers in Sukabumi Regency, West Java, Indonesia," *Journal of Physics: Conference Series*, vol. 1155, no. 1, Feb. 2019, doi: 10.1088/1742-6596/1155/1/012041.
[27] A. Rahmat, M. A. Hamid, M. K. Zaki, and A. Mutolib, "Normalized difference vegetation index (NDVI) in the integration conservation education forest at Wan Abdul Rachman using modis data," *Indonesian Journal of Science and Technology*, vol. 3, no. 1, pp. 47–52, Apr. 2018, doi: 10.17509/ijost.v3i1.10798.
[28] K. Sundaram, K. R. Sri Preethaa, Y. Natarajan, A. Muthuramalingam, and A. A. Y. Ali, "Advancing building energy efficiency: a deep learning approach to early-stage prediction of residential electric consumption," *Energy Reports*, vol. 12, no. 3, pp. 1281–1292, Dec. 2024, doi: 10.1016/j.egyr.2024.07.034.
[29] M. Zhao, S. Gomez-Rosero, H. Nouraei, C. Zych, M. A. M. Capretz, and A. Sadhu, "Toward prediction of energy consumption peaks and timestamping in commercial supermarkets using deep learning," *Energies*, vol. 17, no. 7, p. 1672, 2024, doi: 10.3390/en17071672.
[30] L. Ismail, H. Materwala, and F. K. Dankar, "Machine learning data-driven residential load multi-level forecasting with univariate and multivariate time series models toward sustainable smart homes," *IEEE Access*, vol. 12, no. 3, pp. 55632–55668, 2024, doi: 10.1109/ACCESS.2024.3383958.
[31] D. Desmira, M. A. Hamid, Irwanto, S. D. Ramdani, and T. Y. Pratama, "An ultrasonic and temperature sensor prototype using fuzzy method for guiding blind people," *Journal of Physics: Conference Series*, vol. 1446, no. 1, Jan. 2020, doi: 10.1088/1742-6596/1446/1/012045.
[32] F. Eliza *et al.*, "IoT-based real-time carbon monoxide mitigation for MSME indoor environments," *International Journal of Safety and Security Engineering*, vol. 15, no. 2, pp. 247–256, 2025, doi: 10.18280/ijsse.150205.
[33] S. K. Gautam, V. Shrivastava, S. S. Udmale, A. K. Singh, and S. K. Singh, "Modern machine learning solution for electricity consumption management in smart buildings," *IEEE Engineering Management Review*, vol. 17, no. 1, pp. 1–7, 2024, doi: 10.1109/EMR.2024.3424408.
[34] P. A. Adedeji, S. Akinlabi, N. Madushele, and O. Obafemi, "Hybrid adaptive neuro-fuzzy inference system (ANFIS) for a multi-campus university energy consumption forecast," *International Journal of Ambient Energy*, pp. 1–10, 2020, doi: 10.1080/01430750.2020.1719885.
[35] M. A. Hamid, E. Permata, D. Aribowo, I. A. Darmawan, M. Nurtanto, and S. Laraswati, "Development of cooperative learning based electric circuit kit trainer for basic electrical and electronics practice," *Journal of Physics: Conference Series*, vol. 1456, no. 1, Jan. 2020, doi: 10.1088/1742-6596/1456/1/012047.
[36] X. Zhou, J. Yan, J. Zhu, and P. Cai, "Survey of energy consumption and energy conservation measures for colleges and universities in Guangdong Province," *Energy & Buildings*, vol. 66, pp. 112–118, 2013, doi: 10.1016/j.enbuild.2013.07.055.
[37] A. A. K. Pereira, R. J. A. Menezes, A. Jadidi, P. De Jong, and A. C. d. C. Lima, "Development of an electronic device with wireless interface for measuring and monitoring residential electrical loads using the non-invasive method," *Energy Efficiency*, vol. 13, no. 7, pp. 1281–1298, Oct. 2020, doi: 10.1007/s12053-020-09887-z.
[38] L. J. Qu, L. N. Lei, W. Chen, and J. Y. Qian, "Energy consumption prediction of university buildings in China and strategies for energy efficiency management," in *ASME 2015 9th International Conference on Energy Sustainability, ES 2015, collocated with the ASME 2015 Power Conference, the ASME 2015 13th International Conference on Fuel Cell Science, Engineering and Technology, and the ASME 2015 Nuclear Forum*, 2015, pp. 1–6. doi: 10.1115/ES2015-49071.
[39] K. P. Amber *et al.*, "Energy consumption forecasting for university sector buildings," *Energies*, vol. 10, no. 10, pp. 1–18, 2017, doi: 10.3390/en10101579.
[40] Y. Ding, Q. Wang, Z. Wang, S. Han, and N. Zhu, "An occupancy-based model for building electricity consumption prediction: a case study of three campus buildings in Tianjin," *Energy and Buildings*, vol. 202, 2019, doi: 10.1016/j.enbuild.2019.109412.
[41] H. Im, R. Srinivasan, and S. Fathi, "Building energy use prediction owing to climate change: a case study of a university campus," in *UrbSys 2019 - Proceedings of the 1st ACM International Workshop on Urban Building Energy Sensing, Controls, Big Data Analysis, and Visualization, Part of BuildSys 2019*, 2019, pp. 43–50. doi: 10.1145/3363459.3363531.
[42] T. Zhao, J. Xu, C. Zhang, and P. Wang, "A monitoring data based bottom-up modeling method and its application for energy consumption prediction of campus building," *Journal of Building Engineering*, vol. 35, no. October, 2021, doi: 10.1016/j.jobe.2020.101962.
[43] M. V. Moreno *et al.*, "Big data: the key to energy efficiency in smart buildings," *Soft Computing*, vol. 20, no. 5, pp. 1749–1762, 2016, doi: 10.1007/s00500-015-1679-4.
[44] Y. Tang *et al.*, "An adaptive forecasting method for the aggregated load with pattern matching," *Frontiers in Energy Research*, vol. 10, 2023, doi: 10.3389/fenrg.2022.1088100.
[45] H. Li, G. Feng, D. Zhen, F. Gu, and A. D. Ball, "A normalized frequency-domain energy operator for broken rotor bar fault diagnosis," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, no. 3, pp. 1–10, 2020, doi: 10.1109/TIM.2020.3009011.
[46] A. Azadeh, S. F. Ghaderi, and S. Sohrabkhani, "Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors," *Energy Conversion and Management*, vol. 49, no. 8, pp. 2272–2278, 2008, doi: 10.1016/j.enconman.2008.01.035.
[47] J. H. Park, Y. M. Park, and K. Y. Lee, "Composite modeling for adaptive short-term load forecasting," *IEEE Transactions on Power Systems*, vol. 6, no. 2, pp. 450–457, 1991, doi: 10.1109/59.76686.
[48] D. F. de Souza, P. P. F. da Silva, L. F. A. Fontenele, G. D. Barbosa, and M. de Oliveira Jesus, "Efficiency, quality, and environmental impacts: a comparative study of residential artificial lighting," *Energy Reports*, vol. 5, pp. 409–424, 2019, doi: 10.1016/j.egyr.2019.03.009.
[49] G. Shi, D. Liu, and Q. Wei, "Neurocomputing energy consumption prediction of fi ce buildings based on echo state networks," *Neurocomputing*, pp. 1–11, 2016, doi: 10.1016/j.neucom.2016.08.004.
[50] Y. Ji, Q. Lu, M. Niu, N. Zhang, and J. Xie, "Research on the characteristics and influence factors of residential building energy usage patterns: a case study in Beijing," *Energy for Sustainable Development*, vol. 85, no. 195, p. 101654, Apr. 2025, doi: 10.1016/j.esd.2025.101654.
[51] P. Magdalinos, C. Doulkeridis, and M. Vazirgiannis, "Enhancing clustering quality through landmark-based dimensionality reduction," *ACM Transactions on Knowledge Discovery from Data*, vol. 5, no. 2, pp. 1–44, 2011, doi: 10.1145/1921632.1921637.
[52] J. Yan *et al.*, "Effective and efficient dimensionality reduction for large-scale and streaming data preprocessing," *IEEE Transactions on Knowledge and Data Engineering*, vol. 18, no. 3, pp. 320–332, 2006, doi: 10.1109/TKDE.2006.45.
[53] C. Lee and G. G. Lee, "Information gain and divergence-based feature selection for machine learning-based text categorization," *Information Processing and Management*, vol. 42, no. 1 SPEC. ISS, pp. 155–165, 2006, doi: 10.1016/j.ipm.2004.08.006.

[54] C. J. van Rijsbergen, D. J. Harper, and M. F. Porter, "The selection of good search terms," *Information Processing and Management*, vol. 17, no. 2, pp. 77–91, 1981, doi: 10.1016/0306-4573(81)90029-7.
[55] A. Hyvärinen and E. Oja, "Independent component analysis: algorithms and applications," *Neural Networks*, vol. 13, no. 4–5, pp. 411–430, 2000, doi: 10.1016/S0893-6080(00)00026-5.
[56] D. P. Berrar, W. Dubitzky, and M. Granzow, Eds., *A practical approach to microarray data analysis*. New York: Springer, 2003.
[57] M. Rezghi and A. Obulkasim, "Noise-free principal component analysis: an efficient dimension reduction technique for high dimensional molecular data," *Expert Systems with Applications*, vol. 41, no. 17, pp. 7797–7804, 2014, doi: 10.1016/j.eswa.2014.06.024.
[58] Desmira, N. A. Bakar, M. R. Hashim, R. Wiryadinata, and M. A. Hamid, "Laboratory prediction energy control system based on artificial intelligence network," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 3, pp. 1280–1288, Jun. 2022, doi: 10.11591/EEI.V11I3.1821.
[59] J. Yang, H. Rivard, and R. Zmeureanu, "On-line building energy prediction using adaptive artificial neural networks," *Energy and Buildings*, vol. 37, no. 12, pp. 1250–1259, 2005, doi: 10.1016/j.enbuild.2005.02.005.
[60] Hecht-Nielsen, "Theory of the backpropagation neural network," in *International Joint Conference on Neural Networks*, IEEE, 1989, pp. 593--605 vol.1. doi: 10.1109/IJCNN.1989.118638.
[61] K. Li, C. Hu, G. Liu, and W. Xue, "Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis," *Energy and Buildings*, vol. 108, no. 5, pp. 106–113, 2015, doi: 10.1016/j.enbuild.2015.09.002.
[62] Y. Boujoudar, M. Azeroual, H. Elmoussaoui, and T. Lamhamdi, "Intelligent control of battery energy storage for microgrid energy management using ANN," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 4, pp. 2760–2767, Aug. 2021, doi: 10.11591/IJECE.V11I4.PP2760-2767.
[63] R. Mena, F. Rodríguez, M. Castilla, and M. R. Arahal, "A prediction model based on neural networks for the energy consumption of a bioclimatic building," *Energy and Buildings*, vol. 82, pp. 142–155, Oct. 2014, doi: 10.1016/J.ENBUILD.2014.06.052.
[64] A. Fischer, A. F. Izmailov, and M. V Solodov, "The Levenberg–Marquardt method: an overview of modern convergence theories and more," *Computational Optimization and Applications*, vol. 89, no. 1, pp. 33–67, 2024, doi: 10.1007/s10589-024-00589-1.
[65] X.-L. Luo, L.-Z. Liao, and H. W. Tam, "Convergence analysis of the Levenberg–Marquardt method," *Optimization Methods and Software*, vol. 22, no. 4, pp. 659–678, 2007, doi: 10.1080/10556780601079233.
[66] S. Konstantinidis, P. Karampiperis, and M.-A. Sicilia, "Enhancing the Levenberg–Marquardt method in neural network training using the direct computation of the error cost function hessian," in *ACM International Conference Proceeding Series*, 2015. doi: 10.1145/2797143.2797162.
[67] M. Kim, S. Jung, and J. W. Kang, "Artificial neural network-based residential energy consumption prediction models considering residential building information and user features in South Korea," *Sustainability*, vol. 12, no. 1, Dec. 2020, doi: 10.3390/su12010109.
[68] W. Shouchun and D. Xiucheng, "Predicting China's energy consumption using artificial neural networks and genetic algorithms," *2009 International Conference on Business Intelligence and Financial Engineering, BIFE 2009*, pp. 8–11, 2009, doi: 10.1109/BIFE.2009.11.
[69] S. Mohammad E. Saryazdi, A. Etemad, A. Shafaat, and A. M. Bahman, "Data-driven performance analysis of a residential building applying artificial neural network (ann) and multi-objective genetic algorithm (ga)," *Building and Environment*, vol. 225, no. 2, p. 109633, 2022, doi: 10.1016/j.buildenv.2022.109633.
[70] S. Barak and S. S. Sadegh, "Forecasting energy consumption using ensemble ARIMA-ANFIS hybrid algorithm," *International Journal of Electrical Power and Energy Systems*, vol. 82, pp. 92–104, 2016, doi: 10.1016/j.ijepes.2016.03.012.
[71] F. Rodrigues, C. Cardeira, and J. M. F. Calado, "The daily and hourly energy consumption and load forecasting using artificial neural network method: a case study using a set of 93 households in Portugal," *Energy Procedia*, vol. 62, pp. 220–229, 2014, doi: 10.1016/j.egypro.2014.12.383.

BIOGRAPHIES OF AUTHORS

Desmira is currently a PhD candidate at the Department of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka (UTeM), Malaysia. She is also serving as a lecturer and Assistant Professor in the Department of Electrical Engineering Vocational Education at Universitas Sultan Ageng Tirtayasa (Untirta), Serang, Indonesia. With extensive experience in teaching and research, Desmira has focused her work on several key areas within electrical engineering, including the development of advanced sensors, the integration of artificial intelligence into engineering systems, and innovations in electronics. Her research aims to contribute to technological advancements that enhance the efficiency and functionality of electrical systems, emphasizing practical applications that benefit both industry and education. She can be contacted via email at desmira@untirta.ac.id and p011820005@student.utem.edu.my.

Norazhar Abu Bakar (Member, IEEE) received his BEng. (Hons.) degree in electronics and electrical engineering from Leeds University, UK, MSc. (Eng.) in control systems from Sheffield University, UK, and PhD degree in electrical and computer engineering from Curtin University, Australia. He started his career as an assembly engineer at Toshiba Electronics, Malaysia, and then moved to TNB as a SCADA/DA Project Engineer. Currently, he is a senior lecturer at the Department of Electrical and Electronics Engineering, Faculty of Engineering, Universiti Teknologi PETRONAS. His research interests are condition monitoring, asset management, and artificial intelligence. Since 2013, he has published several articles related to transformer condition monitoring and asset management in IEEE Transactions on Dielectrics and Electrical Insulation and IEEE Electrical Insulation Magazine. He can be contacted via email: norazhar.abubakar@utp.edu.my.

Mustofa Abi Hamid (Member, IEEE) is a doctoral candidate at the Graduate School of Technological and Vocational Education, Universitas Negeri Yogyakarta (UNY), Indonesia. He is also an Associate Professor of TVET at the Department of Electrical Engineering Vocational Education, Universitas Sultan Ageng Tirtayasa, Serang, Indonesia. He has written several papers in the areas of technical and vocational education and training, electrical engineering, artificial intelligence, digital learning, e-learning, evaluation of learning, learning media, and ICT for learning. His research interests also include vocational learning strategies, school-to-work transition, pedagogical innovations in TVET, skills and personal development, innovations in engineering and education, etc. He is a member of the Asian Academic Society for Vocational Education and Training (AASVET) & member of the European Research Network Vocational Education and Training (VETNET). He can be contacted at email: abi.mustofa@untirta.ac.id; mustofa@ieee.org; and mustofaabi.2023@student.uny.ac.id.

Muhammad Hakiki is a lecturer and researcher at the Department of Information Technology Education, Faculty of Engineering, Universitas Negeri Surabaya, Surabaya, Indonesia. He has written several papers in the areas of technology and vocational education (TVET), emerging technologies, engineering education, educational technology, multimedia, and hypermedia applications, technology-enhanced learning (TEL) and learning environments, cybersecurity and privacy in educational technologies, pedagogy and learning issues. His research interests also include developing effective educational strategies and resources, aimed at enhancing teaching and learning experiences in academic and vocational contexts. His work contributes to advancing the use of ICT in education and improving vocational education practices. He can be reached via email: muhammadhakiki@unesa.ac.id.

Affero Ismail is the UNEVOC Centre Coordinator, and an associate professor in the Department of Engineering Education, Faculty of Technical and Vocational Education. He formerly served as the Head of the Department at the Malaysia Research Institute for Vocational Education and Training (MyRIVET). He has a Ph.D. in TVET, a Master of Science in Human Resource Development, and a Bachelor of Engineering in Computer and Communication Systems. He is a professional member of the Malaysia Board of Technologists and Young Scientist Network, Academy of Science Malaysia. His research interests include curriculum development, digitization, training, teaching and learning, professional development, the Sustainable Development Goals, and green skills. He can be contacted at email: affero@uthm.edu.my.

Radinal Fadli is a doctoral candidate in Technology and Vocational Education, Graduate School, Universitas Negeri Yogyakarta (UNY), Sleman, Indonesia. Currently, working as a lecturer and researcher at the Department of Information Technology Education, Faculty of Teacher Training and Education, Universitas Lampung, Bandar Lampung, Indonesia. His research interests include digital learning, online learning, mobile learning, educational media, network technology, and cybersecurity awareness. He can be contacted at email: fadliradinal@gmail.com.