Prediction of Biogas Production from Agriculture Waste Biomass Based on Backpropagation Neural Network

Arief Abdurrakhman[1,2,3*], *Lilik* Sutiarso[1*], *Makhmudun* Ainuri[1], *Mirwan* Ushada[1], *Md Parvez* Islam[3]

[1]Faculty of Agricultural Technology, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia
[2]Department of Instrumentation Engineering, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia
[3]Faculty of Agriculture, Ehime University, Matsuyama, Japan

Abstract. An integral aspect of sustainable agriculture involves the implementation of a meticulously planned waste management infrastructure. One strategy to achieve this objective is the utilization of agricultural waste, specifically in the form of biomass, to generate sustainable energy such as biogas. This study aims to provide valuable prediction model for biogas production with many variables which is influenced. The study identifies four variables, namely pH, moisture content, Organic Loading Rate (OLR) and temperature which significantly impact on the biogas production, especially in Indonesia. Any fluctuations in these variables can affect biogas productivity. Therefore, machine learning techniques such as adaptive backpropagation neural network is used to modeling for predition of biogas production. The configuration of the multilayer perceptron model, combined with the Backpropagation Algorithm, establishes the fundamental framework for the proposed advancements. This study explores three different types of training algorithms in the backpropagation neural network, specifically Adaptive Learning Rate, Levenberg-Marquardt, and Resilient Backpropagation. The Resilient Backpropagation approach exhibited exceptional effectiveness, as evidenced by a correlation coefficient of 0.9411 for training and 0.90423 for testing. The best results obtained for Mean Squared Error (MSE) and Mean Absolute Error (MAE) were 0.0038 and 0.0316, respectively. The Standard Deviation was computed to be 0.0615. This study highlights the potential benefits of employing Resilient Backpropagation Neural Network alghoritm to determine the appropriate operational parameters and accurately predict the biogas production

1 Introduction

Biogas production from agricultural waste biomass presents a promising solution to energy deficits and environmental challenges. This renewable energy alternative not only reduces our reliance on fossil fuels and greenhouse gas emissions but also repurposes waste materials that would otherwise contribute to pollution. The potential of biogas lies in its ability to

* Corresponding author: ariefabdurrakhman@mail.ugm.ac.id and lilik-soetiarso@ugm.ac.id

convert a variety of agricultural by-products into energy, thereby advancing sustainable energy goals and promoting ecological conservation. Biogas production potential biogas is produced through anaerobic digestion of organic substances, mainly producing methane and carbon dioxide. This process can accommodate a broad spectrum of substrates, including agricultural crop residues, which are abundant and varied [1][2]. Agricultural by-products, especially those from greenhouse vegetable cultivation, have shown great biochemical methane potential (BMP), a measure of the amount of methane that can be produced from a given substrate, making them suitable feedstocks for biogas production [3]. Incorporation of co-substrates, such as crop residues together with livestock waste, can increase biogas yield and process efficiency, as evidenced by increased gas production during fermentation of mixed substrates [4] [2]. Biogas production from agricultural waste reduces methane emissions and provides an affordable energy alternative to Liquefied Petroleum Gas (LPG) with financial incentives. [5].

Several important factors, including substrate type, operational conditions, and pretreatment methods, influence fluctuations in biogas production originating from agricultural biomass waste. These elements are essential in determining the efficiency and yield of biogas generation, which is vital for increasing this renewable energy resource. An in-depth study of these factors is presented below. Due to its nutritional profile, the substrate used is essential in determining biogas yield. For example, animal manure shows varying methane yields, with goat and pig manure showing superior results to other variants. Lignocellulosic biomass and municipal solid waste also show variability in methane generation, influenced by their organic content and biodegradability [6]. The temperature of process conditions is a significant variable, with increasing temperature promoting biogas production by increasing microbial activity. Factors such as carbon to nitrogen (C/N) ratio, pH level, and total solids concentration are critical as they impact the microbial ecosystem and digestive efficiency [7]. For instance, adjusting the C/N ratio can be a strategy to optimize biogas production. Additional parameters, including feedstock dilution, retention time, and mixing, can further influence the process, with optimal conditions depending on the feedstock used [1]. Pretreatment methods, such as mechanical, chemical, or biological processes, can improve the biodegradability of substrates, thereby enhancing methane yields. Codigestion, which involves the simultaneous digestion of multiple substrates, can balance nutrient levels and improve overall biogas production efficiency [8].

The development of biogas prediction has been conducted, such as hybrid machine learning algorithm, synthetic minority oversampling technique-genetic algorithm-extreme learning machine (SMOTER-GA-ELM), predicts biogas production in food waste anaerobic digestion using 14 input parameters. It demonstrates a high prediction accuracy with a mean absolute percentage error of 2.15%. The ELM algorithm facilitates real-time monitoring and offers prediction capabilities within 0.8 seconds. The study affirms the predictive efficacy of the hybrid model, emphasizing feed loading and volatile fatty acids as critical factors in biogas yield estimation [9]. A recurrent neural network (RNN) black-box model was developed to predict biogas production rates in dry AD systems, showcasing the potential for system control and optimization. A recurrent neural network (RNN) black-box model was developed to predict biogas production rates in dry AD systems, showcasing the potential for system control and optimization [10]. Artificial neural networks (ANN) are employed to assess biogas production rates. Variable selection utilized various optimization algorithms, including the cuckoo optimization algorithm (COA), multi-verse optimization algorithm (MVO), leagues championship algorithm (LCA), evaporation-rate water cycle algorithm (ERWCA), stochastic fractal search (SFS), and teaching learning-based optimization (TLBO). The algorithms above facilitated the synthesis of a multi-layer perceptron (MLP) [11]. Some of these studies have opportunities for improvement, particularly in addressing data preprocessing challenges that affect model accuracy and longevity. The continuous

retraining of ML algorithms can complicate the selection of optimal algorithms for biogas prediction. It's also important to note that laboratory findings may not directly translate to real-scale operations, necessitating the development of customized algorithms. However, the most pressing issue is the insufficient input data, which can impair traditional ML performance and underscores the urgent need for more data in real-scale applications.

The Backpropagation Neural Network (BPNN), an artificial neural network (ANN), is widely used in various fields. This is due to its ability to model complex relationships and predict outcomes accurately, making it a significant tool. BPNN relies on the backpropagation algorithm for training, which is essential for optimizing network weights and reducing prediction errors. The following sections will discuss the essential components of BPNN, including its architecture, applications, and recent advances. BPNN is structured with one input layer, one or more hidden layers, and one output layer [12]. The backpropagation algorithm, a fundamental aspect of BPNN's functionality, calculates the gradient of the loss function over the network weights. It achieves this by propagating the error backwards from the output layer to the input layer. The algorithm's use of the chain rule of calculus to determine these gradients is a key factor in adjusting network weights and minimizing errors [13].

In this study, a prediction model for biogas production influenced by numerous variables has practical implications for the biogas production field. The study identifies four variables, pH, moisture content, Organic Loading Rate (OLR), and temperature, as significant factors in biogas production. Any fluctuations in these variables can have a profound impact on biogas productivity. Therefore, machine learning techniques such as adaptive backpropagation neural networks are used to model the prediction of biogas production. The configuration of the multilayer perceptron model, combined with the Backpropagation Algorithm, establishes the fundamental framework for the proposed advancements, which can be applied to improve biogas production practices.

2 Material and methods

The data used in this research was obtained from the biogas plant in East Java, Indonesia. The raw materials for biogas, cow dung, and rice straw waste, were the primary sources. Each parameter, including pH, moisture content, OLR, and temperature, was supported by approximately 500 data points. The existing data was carefully divided into 350 for training and 150 for testing, ensuring the robustness of our analysis. In this study, the pH value obtained from the real biogas plant had a range of 6 - 8, moisture content of 60 - 80%, OLR of 53 - 70 kg/m3.day, and temperature of 25 – 40 °C. The biogas production rate value, a key output in this biogas prediction model, varies significantly, with a range of 1,677 - 2,446 m^3/day. To analyze this wealth of information, a Backpropagation Neural Network algorithm model was developed, featuring three robust training functions: Adaptive Learning Rate Backpropagation (traingda), Levenberg-Marquardt (trainlm), and Resilient Backpropagation (trainrp).

The artificial neural network architecture, meticulously designed with four hidden layers, each consisting of 50 neurons, undergoes a rigorous evaluation process. Three training functions, Adaptive Learning Rate Backpropagation (traingda), Levenberg-Marquardt (trainlm), and Resilient Backpropagation (trainrp), are used interchangeably. At each iteration, the network is trained using different training functions, and the training results are meticulously evaluated based on Mean Squared Error (MSE) and Mean Absolute Error (MAE). Once training is complete, the network output for the training and test data is calculated and normalized back to the original scale. The training and testing results are compared with the target through regression graphs and plots of data results, and correlation coefficients are also calculated. The comparison between the MSE and MAE values of the

three training functions for training and testing is displayed in a bar graph, a reliable method that effectively visualizes the performance of each training function.

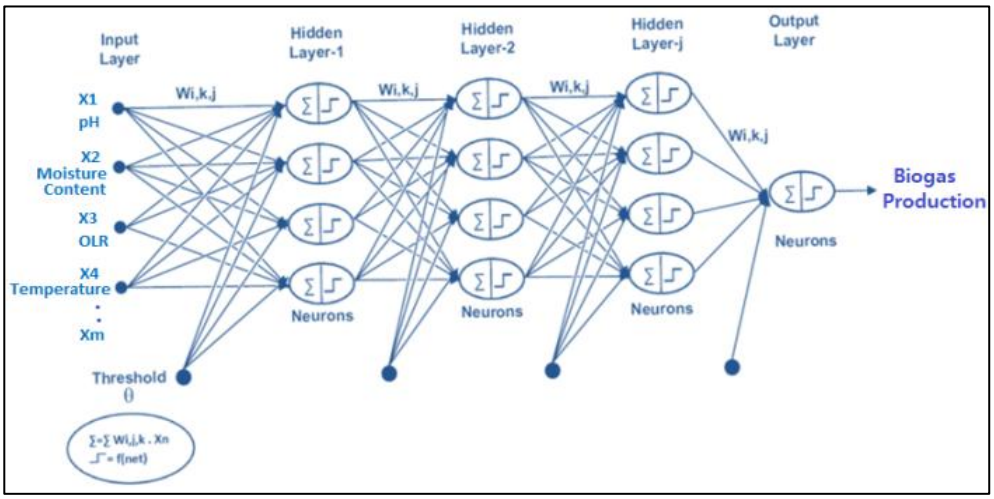

Fig. 1. Topology of MLP Neural Network Model

Figure 1 illustrates that the Multi-Layer Perceptron (MLP) architecture comprises multiple layers, each containing numerous neurons. The initial layer is the input layer, while the terminal layer is the output layer. The intervening layers are referred to as the hidden layers. In forward-pass computation, the input variables or dataset are regarded as independent variables X_i, where i varies from 1 to m (with m representing the total number of independent variables) [14], and each variable encompasses n observations. Following normalization within a defined range, these variables are introduced into the network's input layer. To evaluate the significance of each input, a weight $W_{i,k,}j$ is allocated to the input index i, the preceding layer j-1, the pertinent neuron index k, and the succeeding layer j. The weights were assigned randomly.

The backpropagation algorithm comprises three fundamental stages: training, validation, testing, and forecasting. The dataset was divided into these stages: the predominant portion designated for training, the subsequent segment reserved for assessing the model's accuracy, and the concluding portion for evaluating the model's performance. In the training phase, the backpropagation procedure is succinctly articulated as follows: the weights are modified according to a predetermined learning rate utilizing a learning algorithm that encompasses gradient descent, with adjustments implemented throughout the network upon detecting errors. It is critical to compute the derivative of the error function for each weight and to establish the generalization of the delta rule ΔW. Nonlinearity of the sigmoid function is extensively utilized for normalization purposes within multilayered perceptron architectures. Insufficient normalization of the input variables can markedly undermine the forecasting outcomes [15]. The derivative, represented as $dy/dx = Y$, alongside the delta rule employed to adjust the weight W_i in neuron k of hidden layer j utilizing a sigmoid function, can be delineated as follows:

$$\Delta W_{i,j,k} = \eta X_i \delta_{k,j} \qquad (1)$$

$$\delta_{k,j} = Y_a(1 - Y_a)(Y_d - Y_a) \qquad (2)$$

The weights are subsequently adjusted following the execution of each individual pattern in :

$$W_{i,j,k}\ update = W_{i,j,k} - \Delta W_{i,j,k} \qquad (3)$$

The network utilizes revised weights in the following training cycle. During each cycle, numerous configurations of neurons and hidden layers were assessed to optimize model performance and attain accurate results. The training cycle was deemed complete upon achieving the minimum Mean Squared Error. The Multi-layer Perceptron (MLP) is acknowledged as the most efficacious model and is ready for assessment through comparison with the testing subset of the dataset.

2.1. Adaptive Learning Rate Backpropagation Algorithm for Neural Network Training

Adaptive Learning Rate Backpropagation is a method employed in training neural networks. In this method, the learning rate is altered dynamically throughout the training phase to enhance both convergence velocity and precision. This methodology mitigates the shortcomings associated with static learning rates, which may result in suboptimal training, particularly in intricate or expansive neural network architectures. The adaptive learning rate framework is devised to refine the training procedure by modifying the learning rate based on the behavior exhibited by model parameters and gradients.

Adaptive learning rate strategies, such as those delineated in the Adaptive Backpropagation Algorithm (ABPA), modify the learning rate contingent upon the discrepancies between trained and prospective input datasets. Such modifications attenuate behavioral variances and bolster long-term forecasting precision, as evidenced in electricity load forecasting [14]. Certain adaptive learning rate methodologies, including multivariate adaptive gradient descent, employ a vector-form learning rate to minimize tuning requirements. This paradigm calculates the learning rate grounded in the absolute variances within model parameters and subgradients, resulting in effective convergence with reduced tuning necessities. The core idea is that the learning rate is increased when the network is learning successfully (error is decreasing), and decreased when learning becomes unstable (error increases). The formula for updating the weights w using the adaptive learning rate is [16] :

$$w = w - \eta\frac{\partial E}{\partial w} \qquad (4)$$

Where η is the learning rate, and $\frac{\partial E}{\partial W}$ is the gradient of the error with respect to the weights.

2.2 Levenberg-Marquardt Algorithm for Neural Network Training

The Levenberg-Marquardt algorithm (LM) is a widely used optimization technique for training neural networks, particularly due to its efficiency in handling non-linear least-squares problems. It combines aspects of the Gradient Descent and Gauss-Newton methods to find an optimal set of weights for a network. The formula for the weight update in LM is given as [17]:

$$w_{new} = w - (J^T J + \mu I)^{-1} J^T e \quad (5)$$

Where w is the vector of current weights, J is the Jacobian matrix containing first derivatives of the network errors with respect to the weights, e is the error vector, s the damping factor that controls the transition between Gradient Descent (when μ is large) and the Gauss-Newton method (when μ is small).

If the error decreases after an iteration, the algorithm reduces μ to approach the Gauss-Newton method.

If the error increases, μ is increased to make the optimization more stable, reverting towards Gradient Descent. This combination of techniques makes LM both fast (like Gauss-Newton) and robust (like Gradient Descent), particularly useful for training small- to medium-sized networks.

2.3 Resilient Backpropagation Algorithm for Neural Network Training

Resilient Backpropagation (Rprop) is designed to address issues with vanishing or exploding gradients by focusing on the sign of the gradient rather than its magnitude. The key feature of this algorithm is that it adjusts the step size based on the consistency of the gradient's direction, enabling more stable and efficient training [18]:

$$w_{i,j}^{(t+1)} = w_{i,j}^{(t)} - \Delta w_{i,j}^{(t)} \quad (6)$$

Where $w_{i,j}$ is the weight of the connection between neuron i and neuron j, $\Delta w_{i,j}^{(t)}$ is the update to the weight at iteration t.

3 Results and Discussion

3.1 Correlation Coefficients of Prediction Model

In artificial neural networks or other prediction models, correlation coefficients are often used to evaluate how well the model predictions match the target values. An R-value close to 1 indicates that the model has a good fit [19]. In contrast, a lower R-value indicates an error in prediction or a model that is less accurate in capturing the pattern of relationships between input and output variables. The correlation coefficient is crucial in this study as it provides insight into the quality of the predictions generated by the model [20]. A higher correlation coefficient value indicates better representation of the data by the model's predictions.

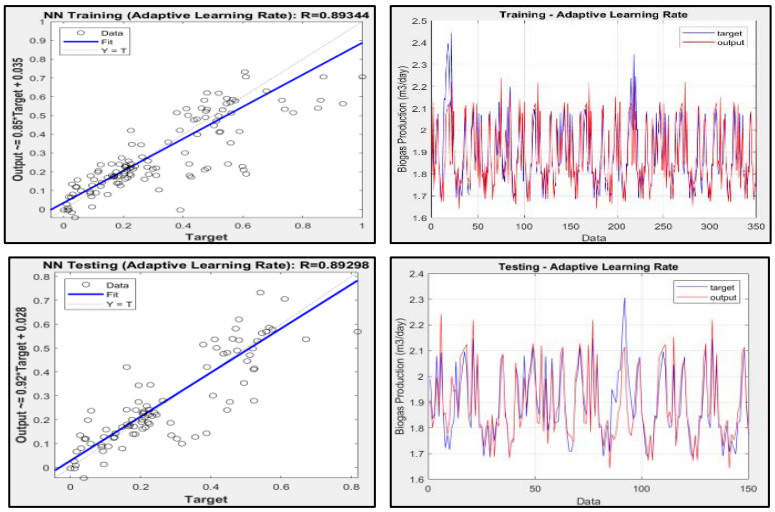

Fig. 2. Training and Testing of the Adaptive Learning Rate

In Figure 2, the correlation coefficient for the Adaptive Learning Rate (ALR) was 0.89344 during training and 0.89298 during testing. These values, which show a positive correlation above 0.8, are key in assessing the model's performance. They indicate that the model captures the relationship between input and output with a value close to 1. However, it's important to note that this correlation is not perfect, meaning there is a deviation between the predicted and actual values. From a theoretical point of view, ALR dynamically adjusts the learning rate during training to optimize the learning process. This practical implication is significant as it allows the network to adapt to variations in gradients and improve convergence. However, it's important to note that this dynamic adjustment, while beneficial, can also cause fluctuations that affect the model's ability to learn more complex relationships with precision. This is evident from the slight decrease in correlation during testing, which shows that this model can be applied in generalization but can still be optimized to be more stable and accurate.

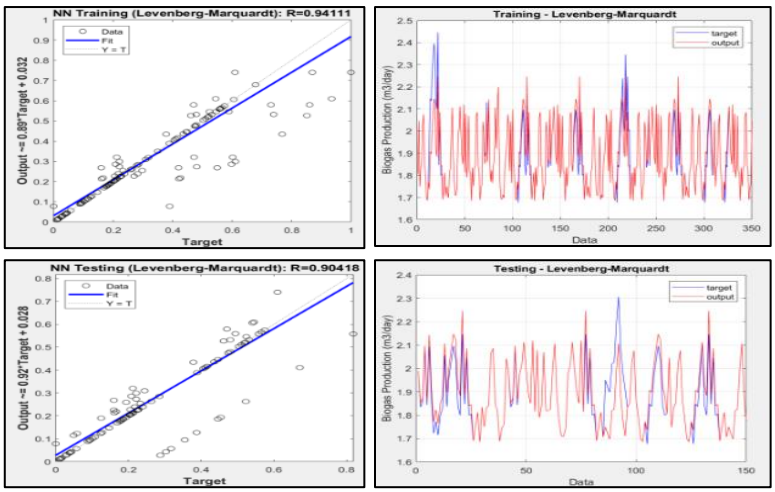

Fig. 3. Training and Testing of the Levenberg-Marquardt

Figure 3 shows that Levenberg-Marquardt (LM) performed better than ALR, with an R-value of 0.94111 during training and 0.90418 during testing. This high R-value, which reflects a strong linear relationship between predicted and actual values, especially during training, should reassure you of LM's effectiveness. It shows that LM can effectively fit the training data, capturing most of the variance in biogas production. LM is known to be effective in solving nonlinear optimization problems, combining the benefits of gradient descent and Gauss-Newton methods. Its superior performance in this context aligns with theory, as LM is well suited to problems where the goal is to minimize errors on large datasets. A slight drop in R during testing indicates slight overfitting, where the model performs slightly worse on data it has not seen before. However, the test correlation remains strong, indicating this model has good generalization ability.

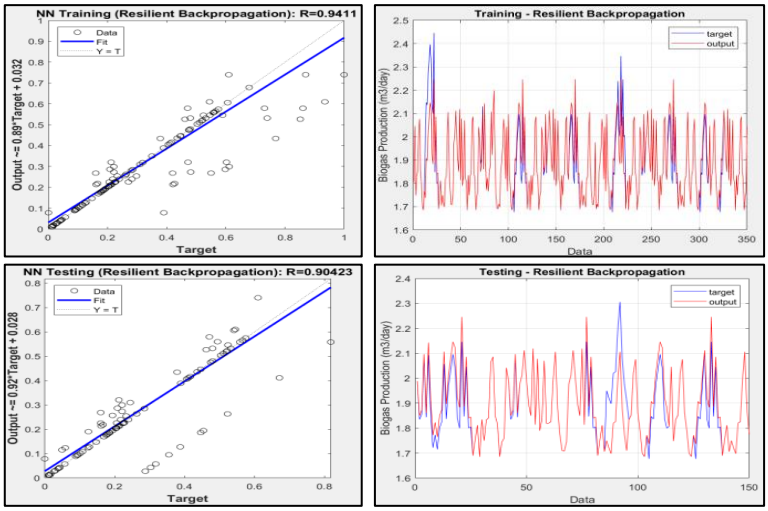

Fig. 4. Training and Testing of the Resilient Backpropagation

Figure 4 illustrate that Resilient Backpropagation (Rprop) performs almost the same as LM, with an R-value of 0.9411 for training and 0.90423 for testing. The R-value, a measure of the strength of the relationship between the input and output, is nearly identical for both LM and Rprop. This indicates that both algorithms effectively learn the relationship between input and output, especially during the training phase. From a theoretical perspective, Rprop's emphasis on gradient direction, rather than magnitude, is a key factor in its stability. This approach helps to avoid issues such as vanishing gradients, ensuring a consistent and reliable performance in both training and testing phases. The slight increase in test correlation compared to LM (0.90423 vs 0.90418) further underscores Rprop's stability and its potential for slightly better generalization.

When comparing these three methods, Levenberg-Marquardt and Resilient Backpropagation outperform Adaptive Learning Rate regarding correlation values. Both LM and Rprop achieve stronger correlations, especially in training, consistent with their theoretical advantages. The LM combination of gradient descent and Gauss-Newton provides faster and more accurate learning, leveraging the benefits of both methods. On the other hand, the Rprop gradient sign approach offers stability and avoids oscillations in the learning process, ensuring a smoother and more efficient learning process. On the other hand, the slightly lower correlation value for ALR suggests that although ALR adapts to the learning process, it may not be able to capture underlying relationships as effectively as LM or Rprop. This implies that ALR, although practical, may not be the best choice for highly accurate

biogas prediction models, especially when compared with more advanced training methods such as LM and Rprop.

3.2 Performance Metrics of Prediction Model

Performance evaluation metrics are critical for assessing the efficacy of predictive models across diverse fields, such as regression analysis, machine learning, and treatment effect forecasting. These metrics furnish quantitative assessments that facilitate the comparison of models and evaluate their predictive precision, calibration, and overall performance. The subsequent sections examine various categories of performance metrics and their relevance in predictive modeling. Mean Squared Error (MSE) is a metric that quantifies the average squared deviation between predicted and observed values, thereby illuminating the model's accuracy. Mean Absolute Error (MAE) is a metric that appraises the average absolute deviation between predictions and actual results, providing a clear and easily interpretable understanding of prediction discrepancies [20]. The standard deviation associated with a predictive model is a crucial measure that indicates the variability or dispersion of prediction errors. This measure is essential for evaluating the model's precision and dependability, two key factors in model assessment. The assessment of standard deviation in these models involves analyzing the distribution of prediction errors, which should exhibit uniformity if the model is valid [21]. Standard deviation aids in pinpointing particular deviations from the model, thereby indirectly offering insights into the variability of predictions.

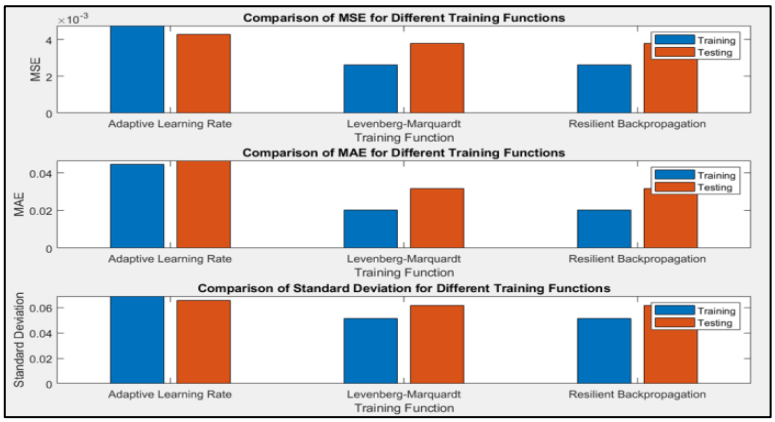

Fig. 5. Performance Metrics of the Adaptive Learning Rate

The Adaptive Learning Rate (ALR) training function exhibits an MSE of 0.0048 and an MAE of 0.0447 during training. These values indicate the average squared and absolute errors, respectively, between the predicted and actual values. The testing phase shows an MSE of 0.0043 and an MAE of 0.0465, which are slightly lower than the training phase. The standard deviation values are 0.0689 for training and 0.0655 for testing, indicating moderate variation in the prediction errors. Compared to the theoretical foundation of ALR, this method dynamically adjusts the learning rate during training based on the gradient. When the error consistently decreases, the learning rate increases; when the error oscillates or worsens, the learning rate decreases. This balance between convergence speed and stability is a key strength of ALR, reflected in the steady performance during testing with slightly lower MSE and MAE than during training. However, the standard deviation is relatively higher, indicating some variability in the predictions, which may result from the fluctuating nature of the learning rate.

The Levenberg-Marquardt (LM) algorithm shows superior performance in both training and testing, with the lowest MSE (0.0026 for training and 0.0038 for testing) and MAE (0.0203 for training and 0.0315 for testing). The standard deviation values of 0.0514 for training and 0.0615 for testing are relatively low, highlighting consistent predictive performance. The LM algorithm, a powerful blend of gradient descent and Gauss-Newton methods, is a marvel of efficiency in optimizing nonlinear most minor squares problems. Its ability to update weights more effectively leads to faster convergence and lower error rates, as evidenced in the results. The lower MAE and MSE compared to ALR underscore LM's knack for finding more accurate solutions in fewer iterations. It is the go-to solution for problems like biogas production prediction, where speed and precision are of the essence.

Resilient Backpropagation (Rprop) performs similarly to LM, with an MSE of 0.0026, an MAE of 0.0204 during training, an MSE of 0.0038, and an MAE of 0.0316 during testing. The standard deviations for training and testing (0.0514 and 0.0615, respectively) are identical to those of LM, indicating that both methods offer stable performance across the dataset. Rprop, unlike standard backpropagation, disregards the magnitude of the gradient and only uses its sign, making it practical for avoiding issues related to vanishing or exploding gradients. This approach leads to stable learning progress, reflected in the low error rates and reduced standard deviation. Rprop's ability to converge quickly without being overly sensitive to gradient oscillations explains its comparable performance to LM, making it a robust alternative.

From the performance results of three types of Neural Network (NN) training functions in the biogas prediction model, Levenberg-Marquardt (LM) emerged as the most reliable option. It demonstrated the lowest Mean Squared Error (MSE) and Mean Absolute Error (MAE) values both at the training stage (MSE: 0.0026, MAE: 0.0203) and testing (MSE: 0.0038, MAE: 0.0315). LM also exhibited a relatively low standard deviation, indicating a high level of prediction stability. Resilient Backpropagation (Rprop) produced results very similar to LM, with almost identical MSE and MAE values, reflecting the stability and ability of Rprop to avoid gradient problems. In contrast, Adaptive Learning Rate (ALR) showed higher MSE and MAE values, with a higher standard deviation, indicating fluctuations in predictions caused by dynamic adjustments to the learning rate. However, the adaptability of ALR suggests potential for improvement. Overall, LM and Rprop proved to be superior in terms of convergence speed and prediction accuracy, while ALR showed good performance but with greater prediction variability.

The development of this biogas prediction model has the potential for larger-scale applications through the use of cloud computing technology and integration with Internet of Things (IoT) devices. By implementing this prediction model on a cloud-based system, data from various geographic locations can be accessed in real-time. This enables more adaptive management of predictions in response to variations in environmental conditions. For instance, IoT sensors can continuously monitor parameters such as pH, humidity, organic loading rate (OLR), and temperature from a biogas plant. This allows the model to update automatically with the latest data, reducing the need for significant manual intervention. On an industrial scale, integrating an automated control system based on Supervisory Control and Data Acquisition (SCADA) can enhance operational efficiency. Furthermore, the model can be improved by using an ensemble learning approach or a hybrid model that combines Resilient Backpropagation with optimization algorithms, such as Particle Swarm Optimization (PSO) or Genetic Algorithm (GA). This hybrid model has the potential to provide better prediction accuracy while reducing computing time. However, the practical application of this model requires careful consideration of the necessary technological infrastructure and operational costs, which may be quite high, especially in rural areas or developing countries. Therefore, further research should focus on developing energy-

efficient and cost-effective prediction systems that utilize lighter algorithms, making them feasible for implementation in resource-limited locations.

4 Conclusion

This study demonstrates the robustness of the Resilient Backpropagation Neural Network (Rprop) in predicting biogas production. With a high correlation coefficient of 0.9411 for training and 0.90423 for testing, as well as a low Mean Squared Error (MSE) value of 0.0038 and Mean Absolute Error (MAE) of 0.0316, this method consistently provides accurate predictions with a low standard deviation, namely 0.0615. The Rprop algorithm's ability to handle variability caused by operational parameters such as pH, humidity, Organic Loading Rate (OLR), and temperature instills confidence in its effectiveness in enhancing biogas productivity.

Implementing an effective waste management system is very important in sustainable agriculture, and utilizing agricultural waste in renewable energy, such as biogas, is one strategy. This study identifies critical variables that influence biogas production, especially in Indonesia. It shows that machine learning methods such as backpropagation-based Neural Networks can help model exact biogas predictions. The integration of multilayer perceptron with backpropagation algorithms, specifically Resilient Backpropagation, presents a robust framework for achieving optimal outcomes in predictive analysis. This approach has proven effective in enhancing the accuracy and reliability of predictions. The potential for further exploration in this field is vast. Future work could delve into ensemble learning-based neural network models or hybrid models that combine Rprop with other optimization algorithms, such as Particle Swarm Optimization (PSO). This could significantly speed up convergence and increase prediction accuracy. Moreover, the addition of data from various geographic sources and different environmental conditions could make the model more adaptive to various global biogas production scenarios. The prospect of applying the Internet of Things (IoT) to obtain real-time data is also exciting, as it could further enrich prediction models and provide more comprehensive solutions to improve energy efficiency in sustainable agricultural systems.

References

1 M. J. B. Kabeyi, O. Oludolapo Akanni, and A. Joseph,Biogas Production and Process Control Improvements, *Intech*, vol. i, no. tourism, p. 15, (2016) [Online]
2 J. Frankowski and W. Czekała, Agricultural Plant Residues as Potential Co-Substrates for Biogas Production, Energies. **16**, 11, (2023). https://doi.org/10.3390/en16114396
3 K. Gioulounta, M. Matska, A. Piskilopoulos, and K. Stamatelatou, Greenhouse Residues' Potential for Biogas Production. Appl. Sci. **13**, 9 (2023). https://doi.org/10.3390/app13095445
4 C. Wang, H. Zhang, J. Liu, J. Sun, and L. Zhao, Effect of hydrothermal carbon on biogas production from agricultural waste by anaerobic fermentation. Highlights Sci. Eng. Technol. **90**, 1 (2024). https://doi.org/10.54097/p2jtyp22
5 B. Singgih, B. Triono, N. Rusdi, M. Ulinuhayani, P. Nurhidayat, and M. Soedarjo, Financial Aspects Of Biogas Production From Livestock Waste To Meet Household Energy Needs. Proc. 1st Int. Conf. Soc. Sci. **3**, 1 (2024). https://doi.org/10.59188/icss.v3i1.207
6 N. Nwokolo, P. Mukumba, K. Obileke, and M. Enebe, Waste to energy: A focus on the impact of substrate type in biogas production, Processes. **8**, 10 (2020). https://doi.org/10.3390/pr8101224

7 M. Saraswat, M. Garg, M. Bhardwaj, M. Mehrotra, and R. Singhal, Impact of variables affecting biogas production from biomass, IOP Conf. Ser. Mater. Sci. Eng. **691**, 1 (2019). https://doi.org/10.1088/1757-899X/691/1/012043
8 A. Kasinath, S. Fudala-Ksiazek, M. Szopinska, H. Bylinski, W. Artichowicz, A. Remiszewska-Skwarek, A. Luczkiewicz , Biomass in biogas production : Pretreatment and codigestion. Renewable and Sustainable Energy Reviews. **150**, 1 (2021). https://doi.org/10.1016/j.rser.2021.111509
9 Y. Zhang, L. Li, Z. Ren, Y. Yu, Y. Li, J. Pan, Y. Lu, L. Feng, W. Zhang, and Y. Han, Plant-scale biogas production prediction based on multiple hybrid machine learning technique. Bioresour. Technol. **363**, 1 (2022). https://doi.org/10.1016/j.biortech.2022.127899.
10 K. W. Seo, J. Seo, K. Kim, S. Ji Lim, and J. Chung, Prediction of biogas production rate from dry anaerobic digestion of food waste: Process-based approach vs. recurrent neural network black-box model. Bioresour. Technol. **341**, 1 (2021). https://doi.org/10.1016/j.biortech.2021.125829
11 Y. Sun, H. liang Dai, H. Moayedi, B. Nguyen Le, and R. Muhammad Adnan, Predicting steady-state biogas production from waste using advanced machine learning-metaheuristic approaches, Fuel, **355**, 1 (2024). https://doi.org/10.1016/j.fuel.2023.129493.
12 S. Damadi, G. Moharrer, M. Cham, and J. Shen, The Backpropagation algorithm for a math student. Proc. Int. Jt. Conf. Neural Networks. (2023). https://doi.org/10.1109/IJCNN54540.2023.10191596.
13 S. Ozbay, Modified Backpropagation Algorithm with Multiplicative Calculus in Neural Networks. Elektron. ir Elektrotechnika, **29**, 3 (2023). https://doi.org/10.5755/j02.eie.34105
14 N. A. Mohammed and A. Al-Bazi, An adaptive backpropagation algorithm for long-term electricity load forecasting. Neural Comput. Appl. **34**, 1 (2022). https://doi.org/10.1007/s00521-021-06384-x
15 G. P. Zhang and D. M. Kline, "Quarterly time-series forecasting with neural networks. IEEE Trans. Neural Networks. **18**, 6 (2007). https://doi.org/10.1109/TNN.2007.896859
16 S. Y. Heng, W. M. Ridwan, P. Kumar, A. N. Ahmed, C. M. Fai, A. H. Birima, and A. El-Shafie, Artificial neural network model with different backpropagation algorithms and meteorological data for solar radiation prediction. Sci. Rep. **12**, 1 (2022). https://doi.org/10.1038/s41598-022-13532-3
17 M. Kiris, I. Demir, and N. Simsek, Comparative Analysis of Neural Networks in the Diagnosis of Emerging Diseases based on COVID-19. Konuralp J. Math. **9**, 2 (2021)
18 A. Mosca and G. D. Magoulas, Adapting Resilient Propagation for Deep Learning, in Proceedings of the UK workshop on Computational Intelligence 2015 (UKCI), September (2015)
19 A. G. Asuero, A. Sayago, and A. G. González, The correlation coefficient: An overview. Crit. Rev. Anal. Chem. **36**, 1, (2006). https://doi.org/10.1080/10408340500526766
20 V. Plevris, G. Solorzano, N. P. Bakas, and M. E. A. Ben Seghier, Investigation of Performance Metrics in Regression Analysis and Machine Learning-Based Prediction Models. World Congr. Comput. Mech. ECCOMAS Congr. (2022)
21 M. F. and E. S., Prediction discrepancies for the evaluation of nonlinear mixed-effects models. J. Pharmacokinet. Pharmacodyn. **33**, 3. (2006).