Scientific Journal of Informatics
Vol. 13, No. 2, May 2026

p-ISSN 2407-7658 https://journal.unnes.ac.id/journals/sji/index e-ISSN 2460-0040

Hybrid Genetic Algorithm and Adaptive Momentum Backpropagation Model with Support Vector Regression Kernel Function for Short-Term Electricity Load Forecasting

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Abstract.
Purpose: Short-term electricity load forecasting (STLF) plays an important role in power system management because electricity demand is dynamic and influenced by factors such as community activities, weather conditions, and seasonal patterns. However, conventional forecasting methods often have limitations in modeling nonlinear and fluctuating electricity load data. Therefore, this study aims to develop a more accurate and stable forecasting model by integrating artificial intelligence methods within a Graphical User Interface (GUI)-based system.
Methods: This research proposes a hybrid model combining Genetic Algorithm (GA), Adaptive Momentum Backpropagation (AMBP), and Support Vector Regression (SVR). GA is used to optimize SVR parameters, SVR performs nonlinear regression forecasting, and AMBP improves learning stability. The dataset consists of electricity load data from Gunung Sari District, Lombok, collected during 2015–2024 with 3,650 daily samples, divided into 80% training data and 20% testing data. Model performance was evaluated using MSE, RMSE, and MAPE.
Result: The experimental results show that the proposed GA–SVR–AMBP hybrid model achieves better forecasting performance than single and partial hybrid models. In the testing phase, the model produced an MSE of 0.1556, RMSE of 0.3945, and MAPE of 1.13%, with an accuracy of 98.86%. Using the entire dataset, the model achieved an MSE of 0.4213, RMSE of 0.6491, and MAPE of 1.6953% with an accuracy of 98.30%, indicating good generalization capability and low prediction error.
Novelty: The novelty of this study lies in the development of a hybrid GA–SVR–AMBP forecasting model integrated into a MATLAB-based GUI system that facilitates data analysis, model execution, and visualization of prediction results for short-term electricity load forecasting and decision support in power system management.

Keywords: Electricity load forecasting, Hybrid genetic algorithm (GA), Adaptive MomentumBackpropagation (AMBP), Support vector regression (SVR), Short-Term forecasting
Received January 2026 / **Revised** March 2026 / **Accepted** March 2026

INTRODUCTION

Short-term load forecasting (STLF) is a crucial element in power system management because demand patterns are dynamic and influenced by various factors, such as daily community activities, weather conditions, temperature, season, and industrial and commercial sector needs [1]. The uncertainty and fluctuations in load demand require accurate prediction models so that system operators can plan power plant operations, schedule unit commitment, regulate power generation economics, and determine spinning reserves more efficiently [2]. Forecasting accuracy is a strategic factor in maintaining grid reliability and stability, as emphasized by [3] that STLF plays an important role in generation scheduling and energy resource optimization. Furthermore, [4] show that forecasting errors can increase operating costs and reduce system reliability. Therefore, STLF not only functions as an estimation tool but also as the foundation for operational decision-making that directly impacts economic efficiency, grid reliability, and the prevention of power outage risks in modern power systems [5].

Various methods have been applied in modeling electricity load data, ranging from classical statistical approaches such as ARIMA, SARIMA, and Holt–Winters, to artificial intelligence approaches such as Artificial Neural Network (ANN), Support Vector Regression (SVR), Random Forest, and Gradient Boosting [6]. Although these methods demonstrate good modeling capabilities, many of them still have

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DOI: https://doi.org/10.15294/sji.v13i2.41475

limitations, such as difficulty in handling complex and nonlinear data patterns, the need for complicated parameter tuning processes, relatively long training times, and sensitivity to noise in the data [7]. In addition, single methods tend to be less stable when applied to datasets with high variability [[8]. This condition necessitates a hybrid approach that can combine the advantages of several algorithms to improve the accuracy and robustness of predictions [9].

Several studies show that Genetic Algorithms (GA) are effective as optimization methods for improving the performance of electricity load forecasting models. Chen et al. (2025) [10] combined GA with ANN and reported a significant reduction in prediction error compared to the baseline model. Ray et al. (2019) [11] also showed a reduction in MAPE values and an increase in overall accuracy in the test dataset. Other studies that utilize GA for network parameter optimization or preprocessing stages report MAPE values in the range of 0.8% to 2.7%, as well as a decrease in RMSE or MAE after optimization. For example, the application of GA for optimizing the initial weights of Extreme Learning Machine (ELM) on regional load data resulted in a MAPE of 0.80%, which is lower than 1.18% without optimization. Additionally, Fida et al. (2024) [12] reported a MAPE of 2.71% and an RMSE of 24.72% for a VMD-BP model optimized using GAs. In general, empirical findings show that GA are consistently able to reduce MAPE and RMSE values, although the magnitude of the improvement depends on the data characteristics and experimental scenario.

Literature that explicitly discusses Adaptive Momentum Backpropagation (AMBP) for STLF is still relatively limited. However, several studies have used variants of adaptive backpropagation or self-adaptive momentum in neural networks and reported improved forecasting performance. Gusti et al. (2021) [13] proposed a Wavelet Neural Network model with a self-adaptive momentum factor and showed significant improvements in MAPE and MSE compared to standard backpropagation. Meanwhile, Zulfiqar et al. (2022) [14] developed the Adaptive Backpropagation Algorithm (ABPA) and reported a MAPE value of 4.5% and an MSE of 1,195,650 on an energy consumption dataset. These findings indicate that adaptive approaches to the learning process can improve convergence stability and reduce prediction errors compared to conventional backpropagation methods [15].

Support Vector Regression (SVR) is also a widely used method in STLF and is generally evaluated using MAPE, RMSE, or MSE metrics. Applied studies report varying MAPE values, depending on data characteristics and preprocessing stages. Resch and Holler (2023) [16] reported a MAPE of 1.085% in a case study of a specific company, while Rabie et al. (2024) [17] reported an average MAPE value of 10.73% on building load data. Hybrid research combining SVR with feature extraction techniques or other models, such as LSTM, also shows improved performance; for example, Hagos et al. (2020) [18] reported a MAPE of 2.32% on an SVR model with fractal features. However, SVR performance is greatly influenced by the choice of kernel, parameters C and γ, and the feature engineering strategy used [19],

Although the GA–SVR, AMBP–NN, and AMBP–SVR methods have been extensively studied separately, studies that integrate these three approaches into a comprehensive hybrid system are still relatively limited [20]. In addition, the implementation of hybrid methods in the form of a Graphical User Interface (GUI) is still very limited [21]. Most studies still rely on manual programming, so the analysis process requires a high level of technical competence from users. This condition indicates an opportunity to develop a prediction system that is not only highly accurate but also easy to use, structured, and capable of displaying analysis results visually [22]. The development of a GUI that integrates several hybrid methods can make an important contribution to simplifying the forecasting process, especially for energy practitioners and researchers [23].

The novelty of this research lies in the development of a GUI-based short-term electricity load forecasting system that integrates Genetic Algorithm (GA), Adaptive Momentum Backpropagation (AMBP), and Support Vector Regression (SVR) into a single integrated hybrid framework. Unlike previous studies that generally apply SVR or two-method hybrid models separately, the proposed approach combines global parameter optimization through GA, stabilization and acceleration of learning convergence through AMBP, and SVR's nonlinear modelling capabilities in a single integrated computing system. The development results show that this system is capable of improving model accuracy and generalization ability, as indicated by a decrease in MSE, RMSE, and MAPE values. In addition, the MATLAB GUI-based implementation provides practical contributions as an analysis and decision-making tool that is easier to use by academics, researchers, and electrical power practitioners.

METHODS

This study uses a quantitative experimental approach to evaluate the performance of the hybrid GA–AMBP–SVR model for short-term electricity load forecasting. The experiment compares the prediction performance of conventional SVR, GA-optimized SVR, and the proposed GA–AMBP–SVR hybrid model using historical electricity load data divided into training and testing datasets. SVR serves as the primary nonlinear regression model, Genetic Algorithm (GA) is used to optimize SVR parameters and generate initial weights for Adaptive Momentum Backpropagation (AMBP), while AMBP refines the prediction results to improve stability and accuracy. Model performance is evaluated using MAE, MSE, RMSE, and MAPE error metrics. The research procedure consists of several main stages, including literature study, data collection, data preprocessing, parameter optimization using Genetic Algorithm, SVR modeling, prediction refinement using Adaptive Momentum Backpropagation, and performance evaluation. These stages are designed to ensure that the proposed hybrid GA–AMBP–SVR model can generate accurate and stable short-term electricity load predictions. The overall research workflow of the proposed forecasting model is presented in Figure 1

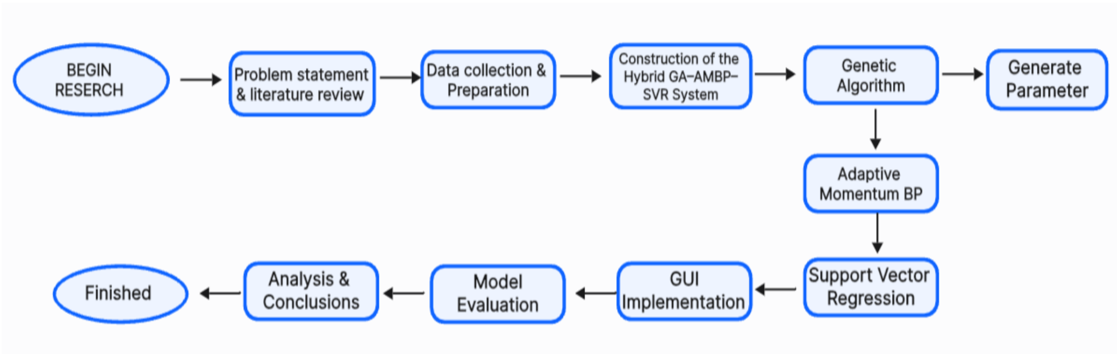

Figure 1. Research flow

Figure 1 shows that the research began with a literature review to identify research gaps related to short-term electricity load forecasting and hybrid machine learning methods. The next step was to collect data from relevant sources containing electricity load data and supporting variables such as temperature, weather conditions, daily activities, and whether the day was a workday or a holiday. The collected dataset then underwent a data preprocessing stage, which included data cleaning to remove missing or inconsistent values, normalization to standardize the scale of variables, and splitting the dataset into training and testing data. After the preprocessing stage, a Genetic Algorithm is applied to generate optimal parameter combinations for the Support Vector Regression model, including the regularization parameter (C), kernel parameter (γ), and epsilon margin (ε). The GA optimization uses several control parameters, such as population size, crossover probability, mutation rate, and maximum generation. The resulting parameters are then used to construct the SVR model to generate initial electricity load forecasts. The prediction results are further refined using an Adaptive Momentum Backpropagation neural network consisting of three layers, namely an input layer, one hidden layer with 10 neurons, and an output layer, in order to improve the stability and accuracy of the forecasts. In the final stage, the forecasting results are evaluated using several error metrics, namely MAE, MSE, RMSE, and MAPE.

Genetic Algorithm (GA)

Genetic Algorithm (GA) is an evolutionary algorithm that mimics the mechanism of natural selection to find optimal solutions through the processes of selection, crossover, and mutation. In this study, GA is used to optimize SVR parameters (C, ε, and γ), produce better initial weights for AMBP, avoid local solutions, and accelerate model convergence. The chromosome representation uses the parameter vector [C, ε, γ], while the fitness function is designed to minimize the MAPE or MSE value, so that the resulting solution can significantly improve the accuracy of short-term electricity load prediction [24]. The fitness function is formulated in equation (1).

$$Fitness = \frac{1}{1 + MSE} \tag{1}$$

The crossover process is performed using uniform crossover, while mutation is performed adaptively to maintain exploration of the solution space. The GA optimization process uses several control parameters, including population size = 50, crossover probability = 0.8, mutation rate = 0.1, and maximum generation = 100.

Support Vector Regression (SVR)

SVR is used to make preliminary predictions of electrical load by projecting data into high-dimensional space using kernel functions. The SVR model minimizes errors within a certain tolerance limit (ε-insensitive loss function) [25]. The SVR prediction function is expressed as equation (2):

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{2}$$

where $K(x_i, x)$ is the RBF kernel function, α_i and α_i^* are Lagrange multipliers, x_i represents the support vectors, and $b$is the bias. Genetic Algorithm is used to find the best SVR parameters, including C(regularization parameter), γ (RBF kernel parameter), and ε(margin tolerance), with the aim of reducing the risk of overfitting and improving the generalization ability of short-term electricity load prediction. In this study, the SVR model uses the Radial Basis Function (RBF) kernel. The parameters C, γ, and ε are optimized using Genetic Algorithm to improve prediction accuracy and model generalization capability.

Adaptive Momentum Backpropagation (AMBP)

AMBP is an extension of the backpropagation algorithm with the addition of adaptive momentum to accelerate learning and stabilize weight changes. The weight update process is expressed by equation (3):

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E}{\partial w_{ij}} + \alpha(t)\, \Delta w_{ij}(t) \tag{3}$$

The previous weight change is defined as:

$$\Delta w_{ij}(t) = w_{ij}(t) - w_{ij}(t-1) \tag{4}$$

The parameter η represents the learning rate, α (t) indicates the adaptive momentum at iteration t, and E denotes the error function calculated using Mean Squared Error (MSE). The weight w_{ij} is the connection weight between neurons in the artificial neural network. The initial weight initialization in AMBP is obtained from the results of Genetic Algorithm optimization so that the training process can avoid local minimum traps and accelerate model convergence [26]. The AMBP neural network architecture used in this study consists of three layers, namely an input layer corresponding to the number of input variables, one hidden layer with 10 neurons, and an output layer with one neuron representing the predicted electricity load value.

The data used in this study is short-term electricity load forecasting data (in MW) which is time series, non-linear, and fluctuating, with supporting variables such as weather, temperature, daily activities, and working days/holidays. The main data was obtained from the NASA POWER database for the Gunung Sari District, Lombok, for a period of 10 years (2015–2024), resulting in a total of 3,650 daily samples, so that it was able to represent the complex dynamics of local electricity load. Before the modeling process, the dataset is divided into 80% training data and 20% testing data, where approximately 2,920 samples are used for training and 730 samples are used for testing. This data division is intended to ensure that the developed model can learn the underlying patterns of electricity load from historical data while maintaining an independent dataset to objectively evaluate prediction performance. As a comparison dataset widely used in the literature on electricity load forecasting [27], this study also refers to electricity load data from the Global Energy Forecasting Competition, which includes historical load data and weather variables for the purpose of evaluating forecasting methods in various public forecasting models. In addition, several studies related to STLF use similar datasets to test and compare the performance of machine learning models in predicting load [28].

RESULTS AND DISCUSSIONS

The data used in this study is short-term electricity load data (MW) recorded periodically at specific intervals throughout the observation period. This data is time series data with fluctuating, nonlinear characteristics and is influenced by various factors such as daily community activities, weather conditions, weekdays and holidays, and consumption patterns in the household, industrial, and commercial sectors. Electricity load data was selected because it is able to represent the dynamics of actual changes in energy demand while also displaying daily and seasonal patterns that repeat throughout the year. To provide an initial overview of the variation in values, general trends, and patterns of increase and decrease in load, the data is presented in tabular form to facilitate the identification of basic characteristics before further analysis is carried out. This descriptive information is an important foundation for understanding the time series structure and ensuring that the data meets the requirements of Hybrid GA–AMBP–SVR modelling. The short-term electricity load forecast data for Gunung Sari subdistrict can be seen in Table 1.

Table 1 Short-Term electricity load forecasting for gunung sari subdistrict

Year	1	2	3	4	5	6	7	8	9	10	11	12
2015	26.37	26.33	26.81	26.8	26.08	25.89	25.94	26.34	27.53	28.71	29.85	28.03
2016	28.34	27.05	28.08	27.75	27.55	26.98	26.26	26.54	28.24	28.32	28.45	26.74
2017	26.32	26.34	26.89	26.92	26.47	25.61	25.70	26.44	27.89	28.38	27.74	26.98
2018	26.20	26.37	26.90	27.26	26.55	26.48	26.26	26.47	27.86	28.69	28.68	27.14
2019	26.67	26.98	26.80	27.13	26.43	25.78	25.78	26.29	27.28	28.95	29.47	29.38
2020	27.80	27.28	27.33	27.42	27.09	26.77	26.41	27.02	28.63	28.36	28.96	26.93
2021	26.49	26.18	26.51	26.52	26.70	26.93	26.55	27.46	27.8	28.34	27.58	27.16
2022	26.33	26.29	27.01	27.29	27.29	26.44	25.93	26.98	28.05	27.57	27.24	27.36
2023	26.71	26.26	26.85	26.68	26.16	26.46	26.39	26.91	27.96	29.89	29.78	28.84
2024	28.02	27.85	27.66	27.62	27.52	27.09	26.68	27.64	29.03	29.65	28.86	27.33

Table 1 shows electricity load data. Furthermore, this study developed a Graphical User Interface (GUI)-based forecasting system in MATLAB 2018b to facilitate the process of analysis, modelling, testing, and visualization of prediction results. This GUI is designed to integrate three main methods Genetic Algorithm (GA), Adaptive Momentum Backpropagation (AMBP), and Support Vector Regression (SVR) as well as a combination of the three in a single computing platform. Through this GUI, users can input data, run the GA parameter optimization process, generate initial predictions with SVR, refine them through AMBP, and compare the performance of each model interactively. The GUI enables time series analysis to be carried out more quickly, in a structured and user-friendly manner, while supporting the research objective of obtaining an accurate and efficient hybrid model. Training and testing results are displayed on Table 2

Table 2. Training and testing data results

Training (80%) data				
Algorithm	MSE	RMSE	MAPE (%)	Accuracy (%)
GA	0.34	0.59	1.92	98.07
SVR	0.17	0.41	1.37	98.62
AMBP	0.25	0.50	1.64	98.35
GA-SVR	0.53	0.72	1.04	98.95
GA-SVR-AMBP	0.26	0.51	0.15	98.84
Testing (20%) data				
Algorithm	MSE	RMSE	MAPE (%)	Accuracy (%)
GA	0.48	0.69	1.94	98.05
SVR	0.76	1.94	6.38	93.61
AMBP	0.61	2.14	6.56	93.43
GA-SVR	0.43	0.66	1.97	98.02
GA-SVR-AMBP	0.15	0.39	1.13	98.86

Table 2 shows that the evaluation results on the 80% training data of the GA-SVR-AMBP model show the best performance, namely the lowest MAPE of 1.15% and the highest accuracy of 98.84%. A small MAPE value indicates that the percentage of prediction errors against the original data is very low, so that this model is able to follow the data pattern well. The SVR and AMBP models also showed fairly good performance, with MAPEs of 1.37% and 1.64%, respectively, and accuracies above 98%. In contrast, the GA-SVR model had the highest MAPE of 2.04% and the lowest accuracy of 97.95%, indicating that the combination of the two methods was less than optimal in the training stage.

The results of the 20% testing data evaluation again show the dominance of the GA-SVR-AMBP model, which obtained the lowest MAPE of 1.13% and the highest accuracy of 98.86%. This shows that this model is not only superior in training data, but also capable of maintaining excellent performance when faced with new data. The GA and GA-SVR models also showed stable performance with a MAPE of around 1.95% and an accuracy of around 98%, indicating fairly good generalization capabilities. In contrast, single neural network-based models such as SVR and AMBP showed a much higher MAPE of 6% and accuracy dropped to around 93%, indicating that these two models were less able to maintain accuracy when tested with different data.

Actual data and prediction approach in the training process

During the 80% training process, the Hybrid GA–AMBP–SVR model gradually adjusts parameters through optimization and adaptive learning mechanisms. The Genetic Algorithm (GA) works first to find the best parameter combination, then AMBP refines the weights and accelerates convergence, while SVR models the nonlinear relationships found in the electricity load data. This entire process is carried out iteratively so that the prediction results are closer to the actual values. The proximity between the actual data and the predictions is measured using error indicators such as MSE, RMSE, MAPE, and Accuracy. Smaller MSE, RMSE, and MAPE values as well as higher accuracy indicate that the model successfully represents electricity load patterns more accurately. In other words, this hybrid approach is designed so that the model can capture data characteristics optimally through a combination of complementary optimization, stabilization, and nonlinear modeling.

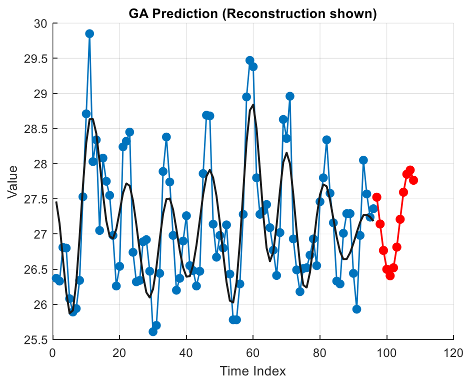

Figure 2. Actual data and prediction approach GA graph

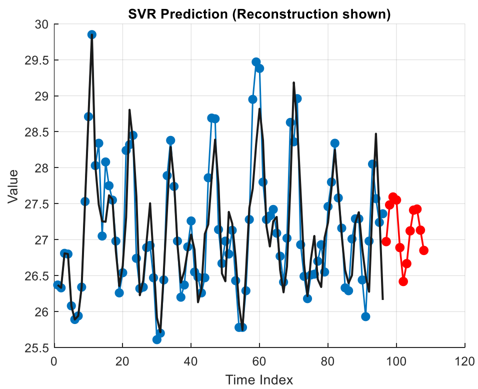

Figure 3 Actual data and prediction approach SVR graph

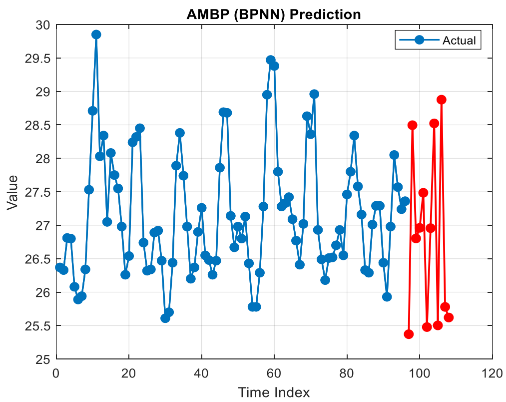

Figure 4 Actual data and prediction approach AMBP graph

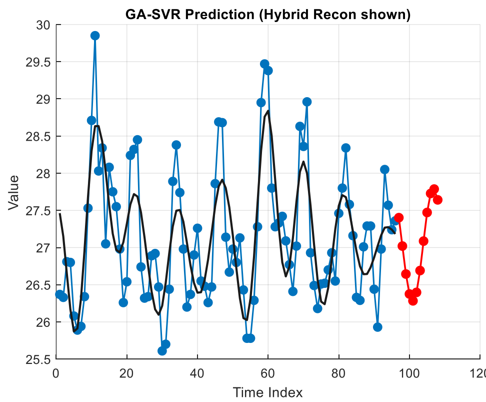

Figure 5. Actual data and prediction approach GA-SVR graph

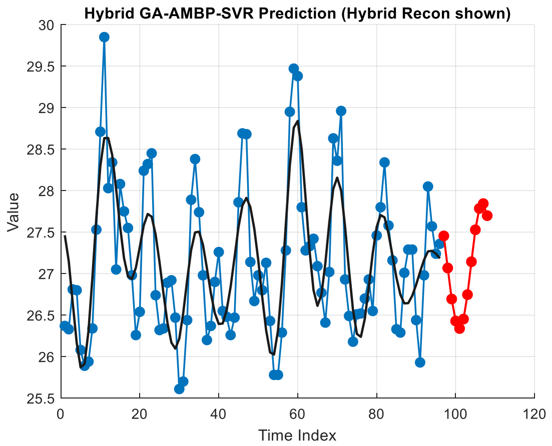

Figure 6. Actual data and prediction approach GA-SVR-AMBP graph

In the training data running results shown in Figures 2 to 6, each model produces different MSE and RMSE values, reflecting the accuracy level of each approach. Figure 2 shows the evaluation results, where this model produces an MSE value of 0.26 and an RMSE value of 0.51. These relatively low MSE and RMSE values indicate that the difference between the predicted values and the actual data is at a low level of error. Figure 3 shows the optimization results using GA, which produced an MSE value of 0.34 and an RMSE value of 0.59, indicating that although GA is capable of global parameter search, its prediction error rate is still relatively higher than other models. Furthermore, Figure 4 shows the performance of AMBP with an MSE value of 0.2586 and an RMSE of 0.5086, which indicates a decrease in error compared to GA, thanks to AMBP's ability to accelerate neural network training convergence Figure 5 shows that the GA–SVR model actually produced the largest error value during the training stage, with an MSE of 0.53 and an RMSE of 0.72, indicating that the combination of these two methods was not yet able to provide optimal results for the running data. Meanwhile, Figure 6 shows the results of the GA–SVR–AMBP hybrid model, which produces an MSE of 0.26 and an RMSE of 0.51, indicating a more stable and balanced error value. The low MSE and RMSE values in this hybrid model indicate that the integration of GA as parameter optimization, SVR as nonlinear modeling, and AMBP as learning process refinement is capable of improving the stability and reliability of the model in the training process. Actual data and prediction approach in the testing process

Actual data and prediction approach in the testing process

During the testing process, the model is tested using 20% of the data that was not used during training to see its generalization ability on new data. The evaluation is carried out by comparing the actual data and the prediction results of each model based on the MSE, RMSE, MAPE, and Accuracy values. Lower MSE, RMSE, and MAPE values indicate lower prediction errors, while higher accuracy values indicate that the model's predictions are closer to the actual data. In the context of GA, SVR, and AMBP methods, this testing stage is very important to ensure that the model not only works well on training data, but also maintains stable and accurate performance when faced with previously unseen data.

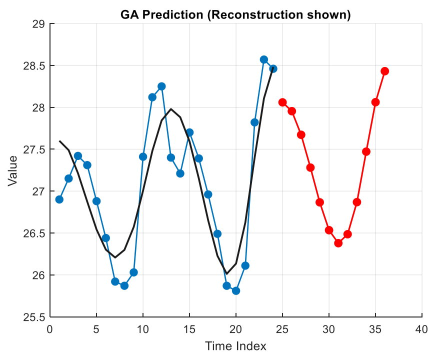

Figure 7. Actual data and prediction approach GA graph

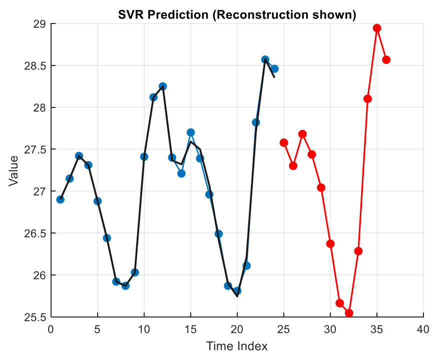

Figure 8. Actual data and prediction approach SVR graph

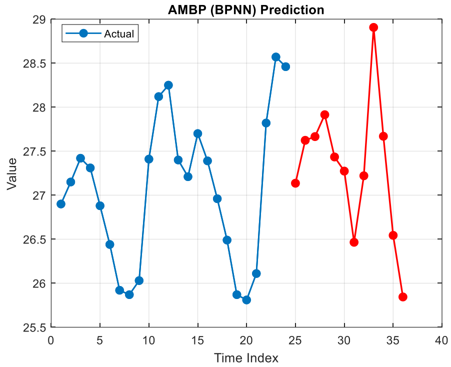

Figure 9. Actual data and prediction approach AMBP graph

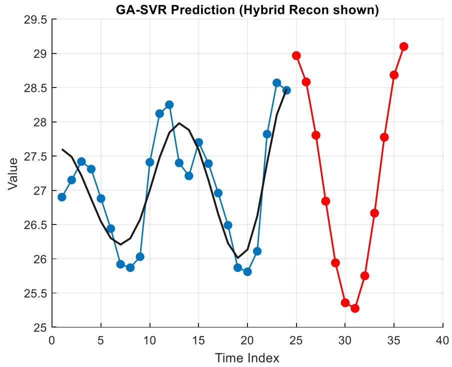

Figure 10. Actual data and prediction approach GA-SVR graph

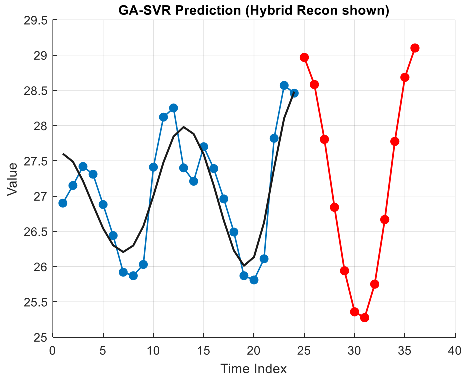

Figure 11. Actual data and prediction approach GA-SVR-AMBP graph

The results of the training data shown in Figures 7 to 11 display the testing results using the GA method, which produced an MSE of 0.4860 and an RMSE of 0.6971, indicating that there is still a noticeable difference between the prediction results and the actual data, so that the generalization ability of GA is moderate. Figure 8 shows the SVR model testing results with an MSE of 0.4379 and an RMSE of 0.6617, which are lower than those of GA, indicating that SVR has better generalization capabilities on untrained data. Figure 9 shows the AMBP method testing results with a significant increase in error, as indicated by an MSE of 3.7660 and an RMSE of 1.9406, making this model less effective in maintaining prediction accuracy in the testing data. Figure 10 shows the testing results of the GA–SVR hybrid model, which produced an MSE of 0.4128 and an RMSE of 0.6428, indicating that the integration of GA as an SVR parameter optimization method was able to reduce the error compared to the single GA and AMBP models, although its performance was not yet optimal. Meanwhile, Figure 11 shows that the GA–SVR–AMBP hybrid model provides the best performance with an MSE of 0.1556 and an RMSE of 0.3945, which are the lowest error values among all models tested, so this model has the most stable and accurate generalization ability at the testing stage.

Actual data and prediction approach

During the training and testing process, the model is tested using 100% of the data. This stage aims to measure the model's ability to generalize new data. The approximation between actual data and predictions is seen from the MSE, RMSE, MAPE, and Accuracy values. The smaller the MSE, RMSE, and MAPE values and the higher the accuracy, the closer the model's predictions are to the actual data in the testing data.

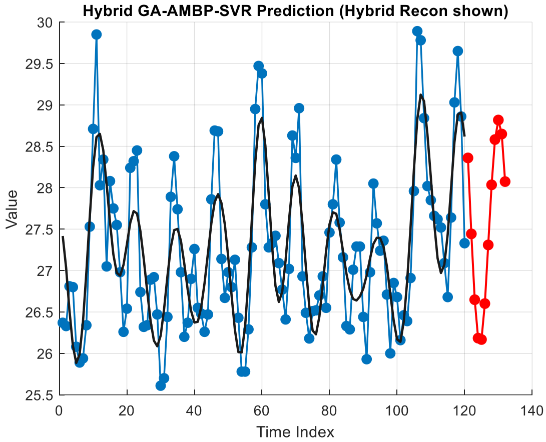

Figure 12. GA-SVR-AMBP training results graph

Figure 12 shows the approximation between actual data and prediction results using the GA–SVR–AMBP hybrid model run with 100% data in the training and testing processes. Based on the evaluation results, this model produces an MSE value of 0.4213, an RMSE of 0.6491, and a MAPE of 1.6953%, with an accuracy rate of 98.30%. The low MSE and RMSE values indicate that the difference between the predicted values and the actual data is relatively small, while the low MAPE value and high accuracy confirm that the prediction results are very close to the actual conditions. This proves that the combination of three methods, namely GA for parameter optimization, SVR as the main prediction model, and AMBP as a learning refinement, is capable of producing the most stable and accurate prediction performance. Thus, the GA–SVR–AMBP hybrid model is the best approach in this study because it provides an optimal balance between low error rates and high prediction accuracy.

The results of training and testing on electricity load data show that the combined GA–SVR–AMBP model provides the most superior prediction performance compared to the single GA, SVR, and AMBP models. The integration of these three approaches allows the utilization of the strengths of each method: GA in global parameter optimization, SVR in capturing non-linear patterns with a stable margin, and AMBP in accelerating learning convergence and maintaining network stability. The combination of the three significantly reduces error values, both MSE and RMSE, making GA–SVR–AMBP the most effective, stable, and reliable model for short-term electricity load forecasting.

The results of monthly electricity load forecasting for 2025 provide an overview of the variation in electricity demand throughout the year, which is influenced by seasonal patterns and the dynamics of community activities. This can serve as an important basis for operational planning of power plants, distribution network management, and mitigation of the risk of power outages during peak load periods [29]. The approach to forecasting electricity load that considers trends, seasonality, and external factors has become the focus of modern forecasting research [30], as models that incorporate seasonal components tend to provide more accurate and informative estimates for decision makers. In addition, statistical methods that model seasonality, such as Seasonal ARIMA, have demonstrated effectiveness in capturing periodic patterns in electricity load data and providing predictions with quantitatively evaluable error metrics. The review of forecasting models also confirms that seasonal and trend components are important aspects that must be considered in STLF [4] to obtain reliable prediction results. The forecasting results in this study show a clear seasonal trend in Gunung Sari District, West Nusa Tenggara, in accordance with the periodic characteristics of electricity load reported in the literature on electricity load forecasting, The forecasting results show that the electricity load in Gunung Sari District, West Nusa Tenggara, has a clear seasonal trend with several months predicted to be in the high load category, which is consistent with previous research findings that seasonal factors, socio-economic activities, and weather conditions play a significant role in shaping monthly electricity load variations. Table 3.

Table 3. Electricity load prediction results using GA, SVR, and AMBP models

MONTH	GA-SVR-AMBP	CATEGORY
Januari	27.28	Currently
Februari	27.01	Currently

Maret	27.56	Currently
April	27.79	Currently
Mei	27.18	Currently
Juni	27.79	Currently
Juli	26.71	Currently
Agustus	27.09	Currently
September	28.61	High
Oktober	29.04	High
November	28.90	High
Desember	28.23	Currently

Table 3 shows the results of the 2025 electricity load prediction using the GA–SVR–AMBP model, which shows a dominant pattern of moderate load from the beginning to the middle of the year, with an increase to high load from September to November. The implications of this pattern are very important for the government, electricity service providers, and the energy industry sector. These prediction results can be used as a basis for planning mitigation policies related to potential load spikes during peak periods that could cause network overload, voltage quality degradation, or planned blackouts. In addition, the industrial and commercial sectors can utilize these predictions to develop more efficient energy management strategies, including managing electricity usage during peak hours. The simulation results confirm that the use of hybrid models can detect patterns of changes in electricity load more accurately, thereby supporting power plant capacity planning, power distribution, and long-term strategic decision-making.

The results of this study indicate that the developed hybrid GA–SVR–AMBP model has superior predictive performance compared to the single Support Vector Regression (SVR) model used in previous studies by [31]. In that study, the SVR model produced a Mean Squared Error (MSE) value of 1.48, whereas in this study, the GA–SVR–AMBP hybrid model was able to significantly reduce the MSE value to 0.2986. This decrease in MSE indicates that the integration of Genetic Algorithm in the parameter optimization process, combined with the ability of SVR to model nonlinear relationships and learning refinement through Adaptive Momentum Backpropagation, can improve the accuracy of electricity load predictions.[25]. This finding confirms that the hybrid approach is more effective in capturing linear and nonlinear patterns in complex time series data than a single model. Thus, the GA–SVR–AMBP model can be a more reliable alternative for short-term electricity load forecasting influenced by seasonal patterns and power system dynamics [32].

CONCLUSION

This study shows that the Hybrid GA–AMBP–SVR model can significantly improve the accuracy of short-term electricity load forecasting compared to single methods. The combination of Genetic Algorithm (GA) for parameter optimization, Adaptive Momentum Backpropagation (AMBP) for learning process refinement, and Support Vector Regression (SVR) as the main prediction model proved effective in capturing complex, fluctuating, and nonlinear electricity load patterns. Based on performance evaluation results, the GA–AMBP–SVR hybrid model produced an MSE value of 0.4213, an RMSE of 0.6491, a MAPE of 1.6953%, and an accuracy of 98.30%, indicating a low prediction error rate and the closeness of the prediction results to the actual data. The implementation of the model in the form of a MATLAB GUI also facilitates the data input, modeling, and visualization of the prediction results. Overall, the results of this study confirm that the GA–AMBP–SVR hybrid model has highly reliable performance and is suitable for use as a decision support tool in the planning and management of electrical power systems. For further research, it is recommended to add external variables such as weather and economic factors, as well as to develop a more adaptive hybrid structure to improve the accuracy of future forecasts

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