A hybrid ARIMA and DNN approach with residual learning for electric vehicle charging demand forecasting

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ABSTRACT

The rapid growth of electric vehicle (EV) adoption has created significant challenges for power grid management and charging infrastructure planning. Accurate forecasting of EV charging demand is therefore essential to ensure reliable electricity supply and effective station deployment. This study proposes a novel hybrid forecasting framework that combines autoregressive integrated moving average (ARIMA) with deep neural networks (DNN) through a residual learning strategy. In this approach, ARIMA models the linear temporal patterns, while DNN captures the nonlinear residuals, resulting in improved efficiency and predictive accuracy. The proposed hybrid model is one of the first applications of the residual learning approach for EV demand forecasting in Indonesia. Experimental evaluation using real-world daily consumption data shows that the hybrid method achieved the highest prediction accuracy of 98.22%, consistently outperforming single-model baselines. Beyond technical performance, the model can support stakeholders in planning charging infrastructure and help maintain grid stability in rapidly growing EV ecosystems.

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1. INTRODUCTION

Electric vehicles (EVs) have gained increasing attention worldwide due to their advantages over fossil-fueled vehicles, including energy efficiency and reduced carbon emissions [1]. EV adoption in Indonesia, encouraging the expansion of charging stations, is crucial to support the government's electrification goals [2]. However, the uneven distribution of electricity supply across regions complicates infrastructure planning and highlights the need for accurate demand forecasting. Accurate EV charging demand forecasting is crucial for many stakeholders. For charging station developers, it supports decision-making regarding site selection and capacity planning. For electric utilities, it ensures alignment between charging demand and electricity supply, especially in regions such as remote islands where generating capacity is limited. Furthermore, reliable demand forecasting can inform national energy policy, including the potential need for additional power generation to sustain a growing EV ecosystem. Given that electricity supply in Indonesia remains uneven across regions, this study focuses on electricity consumption prediction using historical consumption data recorded in the charging station management system (CSMS) [3]. The results of this electricity consumption prediction are very important for entities planning to build new charging stations, as it helps estimate electricity demand that must be aligned with the available power supply in each region. Quantitative forecasting techniques use historical data and various mathematical models containing causal variables to predict demand [4]. Time series forecasting takes this approach further by predicting future events based on historical insights.

Previous research on daily electricity consumption forecasting has explored and compared various machine learning (ML) algorithms. Several studies have analyzed the performance of models such as random forest (RF), support vector regression (SVR), extreme gradient boosting (XGB), and artificial neural networks (ANN) utilizing a multi-layer perceptron (MLP) structure. The results showed that the ANN with MLP architecture achieved the best performance, obtaining an R^2 score of 0.85 and a root mean square error (RMSE) of 115.17 [5], even without incorporating weather-related variables. In a related study, Zhou *et al*. [6] found that the ANN/long short-term memory (LSTM) model outperformed SVR in terms of predictive accuracy. Their research used a Bayesian Deep Learning framework combined with LSTM networks to account for uncertainty in forecasts. This model, trained on actual data from an EV charging station at Caltech, produced an RMSE of around 39.3%, an mean absolute error (MAE) of 42.4%, and showed a 17.9% increase in accuracy compared to SVR. Similarly, research by Kriekinge *et al*. [7] focused on predicting next-day electricity demand at a hospital EV charging station using deep neural networks (DNN), achieving a MAE of 28.8%, marking their highest accuracy. Additionally, Roy *et al*. [8] investigated energy consumption forecasting for EVs using multiple ML techniques, including time series regression, regression-autoregressive integrated moving average (ARIMA), XGB, and ANN with LSTM architecture. Their findings showed that the ANN-LSTM model performed best, with mean absolute percentage error (MAPE) values of 13.14, 15.41, and 31.35 for clusters 1, 2, and 3, respectively.

Based on a review of several previous scientific journals, few studies have investigated hybrid forecasting models that explicitly integrate ARIMA with DNN through residual learning, particularly in the Indonesian context. Addressing this gap, this study proposes a hybrid ARIMA-DNN model with residual learning for predicting daily EV charging demand. This study differs from earlier research by employing a hybrid ARIMA model combined with DNN, leveraging a residual learning approach to further improve prediction accuracy. Historical consumption data from a CSMS are utilized to design the model, which leverages ARIMA for capturing linear temporal patterns and DNN with residual learning for modeling nonlinear components. The objective is to develop a hybrid ARIMA-DNN model with residual learning to predict EV charging load using real experimental data from Jakarta, thereby supporting effective infrastructure planning and electricity management in Indonesia.

2. METHOD

2.1. Approach and technique

This study employs a hybrid model combining ARIMA and DNN to perform time series forecasting using a data windowing or loopback approach. Time series forecasting is a quantitative method used to anticipate future values based on patterns found in sequential historical data [9]. By examining and learning from past trends, this approach facilitates future predictions and helps mitigate potential risks, [10]. As a specialized area within ML, time series forecasting focuses on temporal data, emphasizing the prediction of future values from past sequences. Effective forecasting requires an understanding of several core elements of time series data, including long-term trends (general upward or downward movements), seasonal or cyclic patterns (recurring behavior over regular intervals), irregular fluctuations (often influenced by external events), and random noise (unpredictable variations) [11].

ARIMA, also referred to as the Box-Jenkins model, is widely recognized for its effectiveness in modeling non-stationary time series data [12]. It serves both to enhance understanding of the data and to enable accurate future trend predictions. ARIMA extends the autoregressive moving average (ARMA) model by integrating differencing to handle non-stationarity, and it combines the autoregressive (AR) and moving average (MA) components into a single framework. This model is specifically suited for datasets that are either stationary or can be made stationary through transformation [13]. The complete mathematical formulation of the ARMA (p, q) model is detailed in [14].

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{1}$$

where operator lag B ($\mathrm{B}y_t = y_{t-1}$) d-differencing, written as: $\nabla^d y_t = (1 - B)^d y_t$).
Therefore, the complete ARIMA (p, d, q) formula is (2)

$$\phi(B)(1 - B)^d y_t = c + \theta(B)\varepsilon_t \tag{2}$$

Then, to make it ARIMA (p, d, q), we differenciate it d times (since ARIMA is essentially ARMA after differencing d times). This differencing result is written in your graph as $y_t^{\prime} = (1 - B)^d y_t$. In this context, $y_t^{\prime}$ denotes the differenced time series, which may have undergone one or more differencing operations. The predictors on the right-hand side of the ARIMA equation include both lagged values of the original series of y_t and previous error terms. This formulation is known as the ARIMA (p, d, q) model in (2), where p refers to the order of the AR component, d represents the number of differencing steps applied to achieve stationarity, and q indicates the order of the MA component. ARIMA models can be constructed using either a seasonal or non-seasonal approach, depending on the nature of the time series, with the p, d, and q parameters defining its structure.

After generating the ARIMA forecast y_t', the residuals are calculated as the difference between the actual observation and the forecast, expressed as $e_t = y_t - y_t'$. These residuals represent the nonlinear components not captured by the ARIMA model. In the proposed hybrid framework, the residuals serve as the primary input for the DNN, allowing the network to focus specifically on modeling complex nonlinear dependencies while ARIMA handles the linear structure. Before being used as input to the DNN, the residual sequence undergoes two preprocessing steps. First, a sliding window technique is applied to restructure the residual time series into supervised learning samples, where each window of past residuals is mapped to a future residual value. Second, the data are normalized using min-max scaling to ensure all features are within a uniform range, improving convergence during DNN training. DNN are a branch of ML based on ANN composed of multiple layers hence the term “deep learning.” These networks are capable of learning from and interpreting complex data patterns [15]. DNNs are particularly powerful in modeling how systems respond to changing environmental variables. They are biologically inspired by the structure and functioning of the human brain, where interconnected neurons process and transmit information [13]. This study applies a supervised learning algorithm within the DNN framework. A DNN is architecturally designed to mimic the human brain, consisting of layers of interconnected processing units known as neurons. These neurons form a nonlinear network that processes input data and produces outputs through a sequence of transformations [16].

A typical DNN consists of three main components: an input layer, one or more hidden layers, and an output layer. The hidden layers transform input data into intermediate representations, which are then utilized by the output layer to generate predictions. The outputs from the hidden layers are commonly referred to as activations or nodes. An example of an ANN with a MLP architecture is discussed in [17]. Each neuron in the network receives input signals weighted by specific values. These weighted inputs are summed and then passed through an activation function, which compares the sum to a threshold. If the sum exceeds the threshold, the neuron is activated and passes its output to other connected neurons; otherwise, it remains inactive. This mechanism enables the network to learn and make predictions based on complex input patterns.

2.2. Integration of ARIMA and DNN with residual learning for predictive models

The integration of traditional statistical methods with deep learning models has emerged as a promising direction in time series forecasting. Specifically, the combination of the ARIMA model with DNN, enhanced by residual learning [18], leverages the strengths of both approaches ARIMA’s ability to model linear dependencies and DNN’s capacity to capture complex nonlinear patterns. This hybrid modeling strategy improves forecasting accuracy and generalization, especially for complex real-world time series data such as electricity consumption of EV demand [19]. ARIMA models have long been the cornerstone of time series analysis due to their effectiveness in modeling linear trends and seasonality [20]. However, they struggle with nonlinear and nonstationary data components. In contrast, DNN, especially architectures like MLP, excel at identifying nonlinear dependencies in large and noisy datasets. By integrating these two models through residual learning, the linear components are first captured by ARIMA, and the remaining residual errors, which may contain nonlinear structures are learned by the DNN [21]. The hybrid ARIMA-DNN method follows a two-stage approach that begins with linear modeling using ARIMA to capture the linear components of the time series data. Once the ARIMA model is fitted and generates predictions, the residuals calculated as the difference between the actual data and the ARIMA forecasts are extracted. These residuals, which are assumed to contain the nonlinear patterns not captured by ARIMA, are then used as input to a DNN, such as a multilayer perceptron models, which is trained to learn and predict these nonlinear components. The following is a flow of this research method use the hybrid ARIMA models integrated with DNN with residual techniques.

The ARIMA model parameter values can be determined manually or tuned using the auto_arima function from the Python programming API library [22]. By performing this tuning process with the dataset, the goal is to obtain an optimal ARIMA model tailored to the dataset. Here, p represents the order of the AR component, d is the order of differencing, and q is the order of the MA component. The fact that the tuned differencing (d) parameter is nonzero indicates that the dataset is non-stationary. However, this study also involves manually searching for the optimal ARIMA model parameters to achieve the best model performance. ARIMA modeling is applied to the time series data to capture its linear components, such as trends and seasonality. After the ARIMA model generates forecasts, the residuals calculated as the difference between the actual values and the ARIMA predictions are extracted. These residuals represent the nonlinear patterns that ARIMA could not capture. In the next stage, these residuals are used as input for a DNN, which is trained to model and predict the remaining nonlinear components in the data. To enhance the DNN's ability to recognize temporal patterns, additional input features such as the day of the week (converted to numeric form) may be included.

Figure 1 illustrates a hybrid forecasting approach combining ARIMA and DNN methods to predict daily EV energy demand. The process begins with data collection, where historical daily EV energy demand data is gathered. This is followed by data preprocessing and windowing, where input sequences are created using a window size of 7 days to prepare the data for modeling.

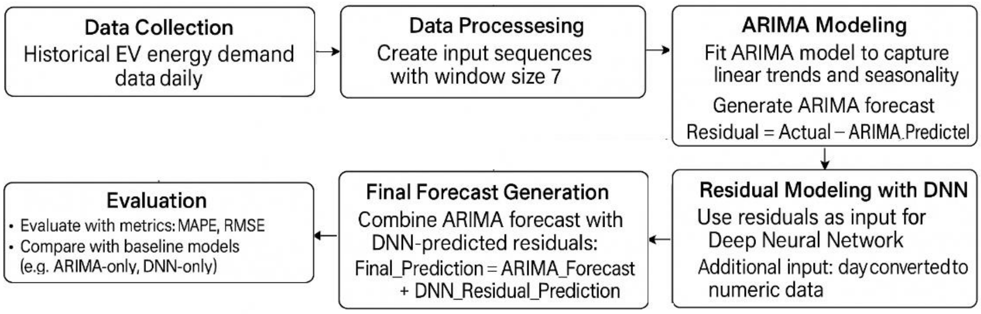


Figure 1. Diagram integration ARIMA and DNN models with residual techniques

ARIMA modeling in Figure 1 is applied to capture linear trends and seasonality, and the residuals calculated as the difference between actual values and ARIMA predictions are extracted. These residuals, along with additional features such as the day converted to numerical format, are used as input for the DNN to model the nonlinear components. The final forecast is generated by combining the ARIMA forecast with the DNN's prediction of the residuals. Finally, the model's performance is evaluated using metrics such as MAPE and RMSE, and is compared against baseline models like ARIMA-only and DNN-only to assess the effectiveness of the hybrid approach.

This study employs a DNN with a multilayer architecture consisting of an input layer, one or more hidden layers, and an output layer. The input layer receives electricity consumption data from the past seven days, which is then processed by the hidden layers to generate predictions in the output layer. Hyperparameter tuning is performed using the Grid Search method to optimize model performance. The number of hidden layers ranges from one to three, with 1 to 150 neurons per layer, and ReLU is used as the activation function. The model is optimized using the Adam optimizer, which adaptively adjusts learning rates based on the training data. The tuning process includes five epochs per trial, repeated 30 times, with learning rates tested at 0.01, 0.001, and 0.0005. The optimal number of epochs is selected based on the lowest MAPE from the validation data.

To prevent overfitting during the training of the hybrid ARIMA–DNN residual learning model, several regularization strategies were applied. Since the ARIMA component already captures the linear temporal dependencies, the DNN is trained only on residuals, reducing the risk of learning redundant patterns. Furthermore, early stopping was implemented with a patience of 10 epochs by monitoring the validation loss and halting training once the performance ceased to improve, thereby avoiding unnecessary iterations that may lead to memorization of noise. In addition, dropout layers with a rate of 0.2 were introduced in the hidden layers of the DNN to randomly deactivate a fraction of neurons during training, which helps prevent co-adaptation among units. L2 weight regularization with a coefficient of 0.001 was also employed to penalize overly complex models, ensuring smoother generalization. The residual inputs were normalized using min–max scaling, which not only accelerates convergence but also stabilizes training, reducing variance across epochs. Finally, the dataset was divided into training, validation, and testing subsets to guarantee unbiased evaluation. Together, these measures strengthen the robustness of the hybrid model, ensuring that the improvements in accuracy are generalizable rather than artifacts of overfitting.

2.3. Data preprocessing

In the data preparation stage, a preprocessing procedure is conducted on experimental data collected from daily electricity consumption of transaction at three different charging stations in Jakarta, Indonesia during 2021–2022. This process involves data cleaning and transformation, as illustrated in Figure 1. The designed predictive model is implemented within the charging station ecosystem and will be integrated with the CSMS application. CSMS serves as the central system for each charging station and can be accessed by users across various regions.

The diagram illustrates in Figure 2 the workflow of an EV charging station ecosystem integrated with a forecasting model for electricity consumption. The process begins with the collection of data from multiple EV charging stations, which communicate using the open charge point protocol (OCPP). These data are stored in a central database and undergo preprocessing, which includes data cleaning, transformation, and splitting into training and testing sets. The data are categorized into two groups: datasets with weather variables and datasets without weather variables. Once preprocessing is complete, the model training and testing phase takes place. This step involves hyperparameter tuning, model training for forecasting electricity consumption, and performance evaluation using metrics such as MAPE or RMSE. The trained forecasting model is then integrated into the system using the database central system, allowing it to predict future electricity consumption. The central system continuously updates and displays new data while also integrating forecast results. These forecasts are used to enhance the efficiency of charging stations by optimizing electricity supply and demand management. The overall system improves the reliability of EV charging infrastructure, ensuring a stable and efficient energy distribution network.

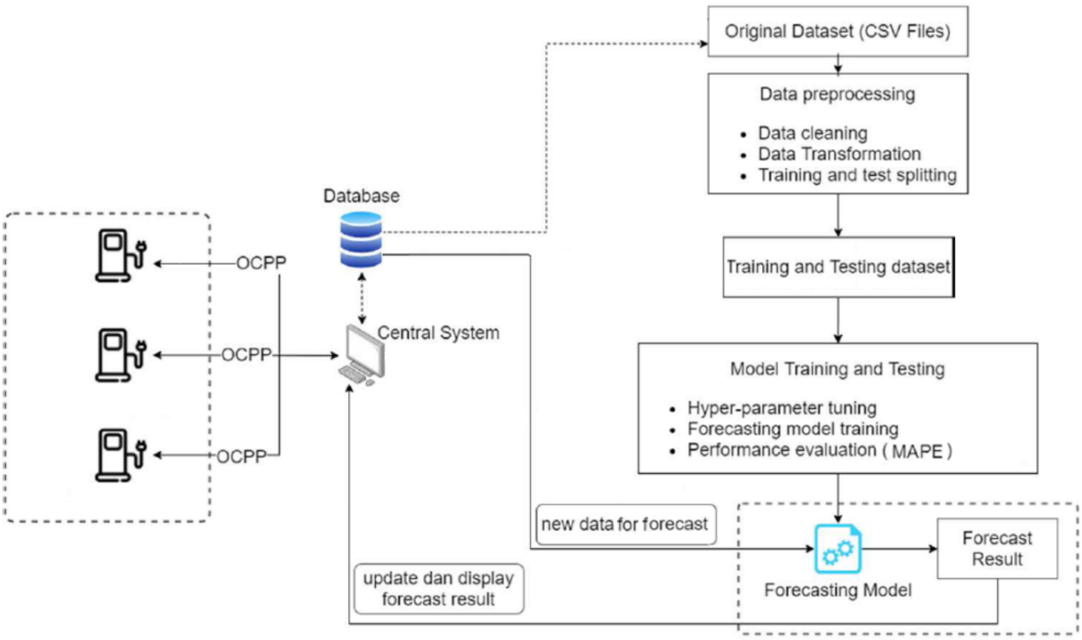


Figure 2. The framework of charging station consumption forecast [5]

The data cleaning process is carried out by selecting one dataset from three charging stations in Jakarta to be used as the primary dataset. Missing data is then filled using the algebraic averaging method, as described in (3), under the assumption that the missing data represents the average consumption of the two nearest charging stations. The algebraic averaging method estimates missing data based on the average data from several nearby charging stations. This approach is formulated using (3) [23].

$$P_X = \frac{P_A + P_B + P_C}{\mathrm{n}} \tag{3}$$

n this study, missing data at charging station X (denoted as P_X) is estimated using data from the nearest charging stations A, B, and C (PA, PB, PC), with n representing the number of stations considered. The data transformation process starts by selecting relevant attributes, which include electricity consumption from the previous seven days (a window size of 7). Additionally, the day of the week is encoded numerically

($Monday = 1$ through $Sunday = 7$). These transformed attributes form the input features, totaling eight, while the electricity consumption for the next day serves as the output label.

2.4. Evaluation

The accuracy of the model will be assessed using the MAPE, which serves to validate its predictive performance. MAPE quantifies relative error by calculating the percentage difference between predicted and actual values. This metric is especially beneficial when the scale of the predicted variable plays a critical role in evaluating forecast precision. As a widely used loss function in regression tasks, MAPE offers an intuitive understanding of prediction errors in relative terms [24]. Expressed as a percentage, it reflects the average deviation between actual and predicted values. MAPE is commonly applied in time series analysis to evaluate forecasting accuracy. The formula for MAPE is presented (4) [25].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{y\_i - \hat{y}\_i}{y\_i} x100\% \quad (4)$$

where the variables in (4) are defined n is the number of samples in the dataset, y_i is the actual value, and $\hat{y}_i$ is the predicted value.

3. RESULTS AND DISCUSSION

3.1. ARIMA modeling

In this study, the dataset of EV charging demand is predicted using the ARIMA model, which is effective when the historical data exhibits a linear and/or consistent seasonal pattern. ARIMA performs well on stable time series data that is not heavily influenced by complex external factors. Daily or weekly EV demand often shows recurring patterns, making ARIMA quite effective for short-term demand forecasting when the EV charging data has sufficiently stable historical patterns. In such cases, ARIMA can be used as a baseline prediction model. However, there are limitations. ARIMA is less optimal when the demand pattern is highly non-linear and influenced by many external variables such as weather, electricity prices, promotions, or specific events. In such cases, hybrid models are used to handle more complex non-linear data, such as DNN, which are more adaptive to external (exogenous) factors and typically produce more accurate results. In this study, to address the complexity of determining the optimal parameters (p, d, q), the $auto\_arima$ function from the $pmdarima$ library is used, as it automatically evaluates various parameter combinations using information criteria (such as Akaike information criterion (AIC) or Bayesian information criterion (BIC)) to select the best model [26]. The division of the dataset into training and testing sets significantly affects the accuracy of the ARIMA model, as it relies heavily on the chronological order of data in a time series. ARIMA learns from past patterns (such as trends and seasonality) to forecast the future. Therefore, if the data is split randomly (non-chronologically), the predictions become invalid and the accuracy decreases. In the ARIMA model evaluation, various combinations of parameters p, d, and q were tested to find the optimal configuration. The dataset was split into different train-test ratios (60:40, 70:30, 80:20, and 90:10) to assess model performance. Using MAPE as the evaluation metric, the best result was achieved with a 90:10 split, where the ARIMA (6, 3, 2) model produced the lowest error, with a MAPE of 16.49%. This indicates that ARIMA (6, 3, 2) is the optimal configuration for this dataset.

In this stage, an ARIMA model is applied to the time series data energy demand EV to capture its linear components, such as trends and seasonality. Once the ARIMA model is trained and makes forecasts, residuals are calculated. These residuals represent the unexplained part of the data specifically, the nonlinear patterns that ARIMA could not capture. The residual is the difference between the actual observed value and the prediction made by the ARIMA model. These residuals as input for a DNN to model the nonlinear relationships in the data. Since ARIMA has already modeled the linear part, the DNN focuses on learning the complex, nonlinear structures that remain in the residuals. Together, this two-step modeling process enhances forecast accuracy by hybrid ARIMA-DNN method gets combining the strengths of ARIMA for linear trends and DNN for nonlinear dynamics.

3.2. Residual modeling with deep neural networks

The residual model with DNN is developed through a systematic hyperparameter tuning process to obtain optimal parameters for the MLP architecture. After fitting the ARIMA model, the residuals defined as the difference between the observed values and ARIMA predictions are extracted. These residuals are first normalized to a standard scale and processed using a sliding window approach to generate sequential input-output pairs suitable for DNN learning. This ensures that temporal dependencies in the residual patterns are preserved. To further enrich the input representation, categorical features such as the day of the week (encoded as numeric 1-7) are integrated, allowing the network to capture periodic nonlinear variations in the charging demand.

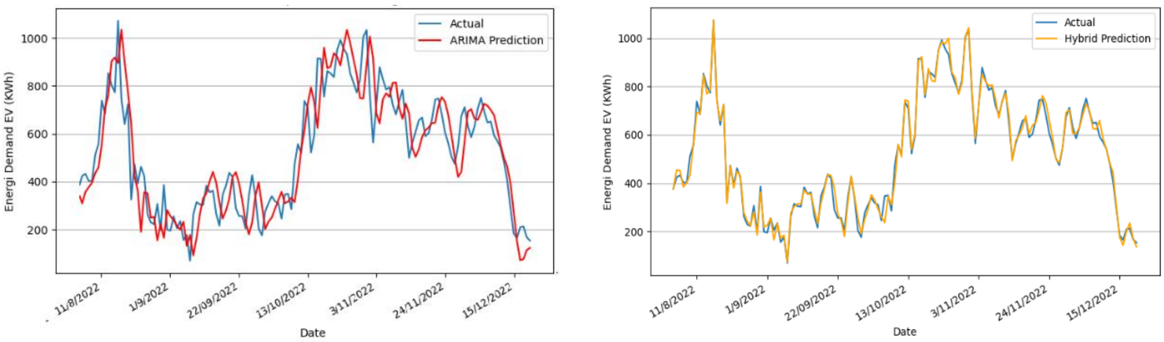
The use of the DNN is motivated by its strong capability to model nonlinear and non-stationary components that cannot be effectively captured by ARIMA alone. A grid-based hyperparameter tuning strategy was conducted to optimize the number of hidden layers, neuron counts, learning rate, and training epochs. Specifically, models with one to three hidden layers were evaluated across different train–test split ratios (90:10, 80:20, 70:30, and 60:40). The tuning process incorporated overfitting mitigation techniques such as early stopping, dropout regularization (0.2-0.5 across hidden layers), and L2 weight penalties, ensuring the model generalizes well to unseen data.

The best-performing configuration was obtained with two hidden layers consisting of 64 and 32 neurons respectively, a learning rate of 0.001, ReLU activation functions, a dropout rate of 0.3, and 1,500 training epochs under a 90:10 split ratio. This configuration achieved a MAPE of 0.39% on the residual forecasting task, confirming that the residual-based DNN not only effectively complements ARIMA but also significantly enhances predictive accuracy by capturing complex nonlinear dynamics.

3.3. Final forecast generation hybrid ARIMA-DNN

The final forecast generation in the hybrid ARIMA-DNN residual learning approach involves combining the strengths of both linear and nonlinear modeling to produce a more accurate prediction. The ARIMA model is used to forecast the linear components of the time series data, such as trends and seasonality. The residuals calculated as the difference between the actual values and the ARIMA predictions are obtained. These residuals, which represent the nonlinear patterns not captured by ARIMA, are then used to train a DNN. ARIMA models capture linear trends, while DNNs handle complex nonlinear patterns. In this hybrid approach, the DNN learns to predict the residuals from the ARIMA model. This division of tasks reduces the risk of overfitting in the DNN. The final forecast is obtained by combining both models using the formula is the final prediction is obtained by adding the forecast from the ARIMA model with the residual prediction generated by the DNN model. This combination leverages the complementary strengths of both models to improve overall prediction performance.

Figure 3(a) shows that the ARIMA (6, 3, 2) model can follow the general trend of EV charging demand, but fails to capture short-term fluctuations and sudden peaks, resulting in a relatively high MAPE of 16.49%. In contrast, Figure 3(b) shows the hybrid ARIMA-DNN model, whose predicted values are much more closely aligned with actual demand, and successfully track both long-term trends and nonlinear variations. By combining ARIMA's advantage in modeling linear patterns with DNN's ability to capture nonlinear residuals, the hybrid model achieves significantly better accuracy, as reflected by its lower MAPE of 1.78%. Table 1 compares this with other comparable deep learning methods.



(a) (b)

Figure 3. Evaluation: (a) ARIMA prediction vs actual and (b) hybrid ARIMA-DNN prediction vs actual

Table 1. Forecasting best accuracy comparison

Model	MAPE (%)	RMSE (kWh)	MAE (kWh)
ANN-MLP	13.89	111.47	94.73
LSTM	13.03	88.66	75.37
ARIMA-DNN (residual-based)	1.78	12.07	10.26

Table 1 compares the forecasting accuracy of the proposed ANN-MLP, LSTM, and hybrid ARIMA-DNN (residual-based) models. As shown in Figure 3(a), traditional ARIMA is effective for long-term trends but struggles with nonlinear fluctuations, while ANN-MLP and LSTM provide better accuracy but remain less consistent. In contrast, the hybrid residual learning approach effectively captures both linear and nonlinear dynamics, achieving the best overall performance with a MAPE of 1.78%, an RMSE of 12.07 kWh, and a MAE of 10.26 kWh, making it the best-performing model compared to single-model approaches and achieving better forecasting accuracy compared to using only ARIMA, ANN-MLP, or LSTM. Notably, the hybrid ARIMA-DNN consistently outperforms the sequence-based LSTM benchmark, highlighting its robustness and suitability for EV charging demand forecasting. The difference between the proposed model and the ARIMA-ANN hybrid (discrete wavelet transform (DWT)-based) [10] in previous research lies in its integration strategy. The DWT-based method decomposes the series into frequency components, while ARIMA-DNN uses residual learning, which allows ANN to directly model the nonlinear errors left by ARIMA. This design improves efficiency and accuracy, with empirical results confirming that ARIMA-DNN provides superior performance (MAPE 1.78%) compared to the DWT-based ARIMA-ANN hybrid (MAPE 1.94%), demonstrating its power in capturing complex nonlinear demand patterns in real-world EV charging data.

From a computational perspective, the hybrid ARIMA–DNN model remains efficient because ARIMA provides fast linear component estimation, thereby reducing the residual complexity fed into the DNN. This decomposition helps shorten training time compared to training a standalone deep model on the full raw data. While DNNs typically require higher computational resources, the residual learning design allows the network to focus on nonlinear patterns with fewer parameters, improving both convergence speed and inference efficiency. In terms of real-time applicability, the ARIMA component can be updated incrementally with minimal overhead, and the trained DNN can generate predictions in near real time once deployed. This makes the hybrid framework suitable for integration into EV CSMS, where accurate demand forecasting must be performed continuously to support dynamic scheduling, energy distribution, and grid stability.

Although the proposed hybrid ARIMA–DNN residual learning model demonstrates strong predictive performance, its generalization is constrained by the dataset, which is limited to daily consumption data collected from only three charging stations within a single region. This restriction may affect the model’s ability to represent broader charging behaviors across different areas with varying infrastructure and user demand. To improve robustness, future studies should validate the framework on larger and more diverse datasets covering multiple charging stations and geographical contexts. Furthermore, extending the model to a multivariate forecasting framework would enhance its applicability. By incorporating exogenous variables such as weather conditions, traffic density, or dynamic electricity pricing, the model could capture external influences on EV charging demand more effectively. Such improvements would not only strengthen predictive accuracy but also support real-world decision-making in complex and evolving energy ecosystems.

4. CONCLUSION

According to the findings of this research and the comparison of the visual results of the graphs and performance metrics shown, the hybrid ARIMA-DNN model shows a much better forecast accuracy than single models. This study confirms that the proposed hybrid ARIMA-DNN model with residual learning outperforms single-model approaches by effectively capturing both linear and nonlinear patterns in EV charging demand. The hybrid method demonstrates its strength in producing more accurate and stable forecasts, making it a reliable tool for energy demand prediction. Beyond technical improvements, the findings provide practical value for stakeholders. Accurate demand forecasting can assist stakeholders in balancing electricity load, support charging station developers in planning infrastructure capacity, and guide policymakers in formulating strategies for national EV deployment, particularly in regions with limited power supply. For future research, the model can be enhanced by incorporating exogenous variables such as weather, traffic flow, or socio-economic data to improve prediction robustness. Further exploration of distributed learning frameworks may also broaden applicability across multi-operator EV charging in Indonesia.

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AUTHOR CONTRIBUTIONS STATEMENT

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

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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author due to privacy and confidentiality restrictions. The dataset is restricted for research purposes under the National Research and Innovation Agency (BRIN) and cannot be shared publicly without prior authorization.

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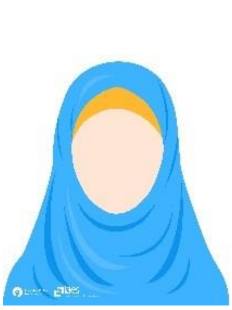

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