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Enhancing Energy Consumption in Automotive Component Manufacturing: A Hybrid Autoregressive Integrated Moving Average–Long Short-Term Memory Prediction Model

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Abstract: The automotive industry faces continuing challenges with regard to advancing sustainability and reducing energy consumption and vehicle emissions. South Africa accounts for half of the total CO₂ emissions in Africa and is the world's 12th-largest CO₂ emitter. In this study, we aimed to develop a model combining autoregressive integrated moving averages (ARIMAs) with long short-term memory (LSTM) to determine the best fit for prediction using the lowest root mean square error configuration and enhance energy consumption in automotive component manufacturing. The ARIMA model dissects time-series data into the components of level, trend, and seasonality, while the automatic ARIMA function refines the model parameters. Simultaneously, utilizing historical data, the LSTM model uses specific algorithms to predict future electricity generation and carbon emissions for the automotive component's manufacturing sector. According to our results, the predicted variables' interdependence revealed an enhancement in energy intensity for vehicle body part products equal to 29%, a cumulative energy savings of 7.22%, and an increase in energy efficiency equal to 16.25%. Our model's predictive fitness holds significant potential for allowing automotive component manufacturers to make informed economic and technical decisions toward the development of low-carbon products. Critically, improved energy efficiency in automotive component manufacturing activities is critical for lowering energy consumption, greenhouse gas emissions, sustainable transportation, and production costs.

Keywords: recurrent neural networks; ARIMA-LSTM; automotive component manufacturing; predictive modeling; sustainable transport



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1. Introduction

The rate of climate change has outpaced earlier predictions made for industrialized and emerging industrialized nations in terms of confronting greenhouse gas emissions, as evidenced by the Intergovernmental Panel on Climate Change (IPCC) [1]. According to IPCC predictions, atmospheric CO₂ levels are anticipated to grow by 2% annually [2]. Given that the manufacturing sector ranks high among major electricity consumers and greenhouse gas emitters, there is a global imperative to reduce emissions by 45% by 2030 (relative to 2010 levels), with a suggested substantial decrease in CO₂ emissions by 2050 [3,4]. Greenhouse gases, primarily carbon dioxide, have been identified as the key contributors to climate change, constituting the majority of overall emissions [3,5]. Due to its energy-intensive operations, the automotive manufacturing industry is not exempted from contributing to climate change mitigation, though it continues to emit greenhouse

gases. South Africa is the world's 12th-largest CO₂ emitter, contributing approximately half of all CO₂ emissions in Africa [6]. The intricate relationship between energy use and climate change is evident in the country's transition from Business-As-Usual (BAU) targets for 2020 and 2025, as outlined in the UNFCCC's Cancun Agreement, to the adoption of absolute greenhouse gas (GHG) emission targets in 2021. This shift signifies reductions of 17% and 28% in the upper bounds of its 2025 and 2030 goals, respectively [7]. Notably, South Africa's automobile manufacturing sector, the largest individual sector in the economy, contributes significantly, accounting for 17.3% of the nation's total car and component output. Alarming findings from the South African National Greenhouse Gas Inventory reveal that this sector is the fastest-growing source of GHG emissions, responsible for approximately 10.8% of the nation's total GHG emissions [8,9]. The recent extension of load shedding announced by Eskom in 2023 underscores the urgent need for a sustainable strategy to manage energy usage and curb carbon emissions. Addressing the heightened energy consumption in manufacturing industries, particularly in the context of embedded energy and CO₂ emission efficiency in product design, remains an uncommon practice. The failure to integrate automobile manufacturing with rapidly advancing technology for efficient decision making in managing energy consumption and carbon emissions poses a significant risk of falling short of established targets, thereby heightening the threat of climate change.

Proposed Innovation—Study Contribution

The automobile manufacturing sector's failure to integrate advanced technology in managing energy consumption and carbon emissions for efficient decision making poses a risk. It also falls short of established targets and heightens the threat of climate change. This study's contributions are as follows:

(1) The authors propose an inverse error combination method, a hybrid of linear and nonlinear models, to enhance energy consumption for South African automotive vehicle component manufacturing plants by estimating the electricity generation and carbon emissions. The joint optimization of linear and nonlinear models for sequential regression is a novel technique [10]. Linear models are preferable due to their low computational complexity and robustness with limited constraints; however, in practical applications, the data exhibit nonlinear attributes, potentially making the latter insufficient [11,12]. Mixed models are extensively represented in the data-processing and deep learning literature, as they promote diversity and dependability by integrating several models, including linear and nonlinear types [13,14].

(2) This study developed a refined ARIMA-LSTM prediction model using a weighted mixture of a linear model (ARIMA) and a nonlinear model (LSTM), aiming to enhance the accuracy of energy consumption and usage projections in the South African automotive component's manufacturing sector. Collective models integrate the predictions of various base models, with each base model uniquely optimized for the underlying data. Consequently, challenges of underfitting and overfitting remain for linear and nonlinear models, respectively [10]. A different mixed-model strategy aimed at mitigating these issues involves integrating the ARIMA and LSTM models by fitting the former to the residuals of the latter. This combined approach aims to provide more precise forecasts related to electricity generation and carbon dioxide emissions, facilitating the transition toward low-carbon products. These low-carbon products, identified from the carbon signature of manufactured items, have potential for adoption in transport manufacturing and could contribute to minimizing the carbon footprint associated with products. Transportation consumes significant energy resources. Improving infrastructure and vehicle architecture and modeling user and driver behavior can contribute to energy savings [15]. The hybrid

ARIMA-LSTM predictive model introduced in this study is a potent tool for automotive component manufacturers. It empowers them to make well-informed decisions by guiding the development of low-carbon products, influencing strategies for future transport manufacturing, and proficiently managing the comprehensive carbon footprint linked to manufactured goods. This study proposes an approach for enhancing energy consumption and usage in South Africa's automotive component manufacturing sector using a hybrid ARIMA-LSTM prediction model. This article is structured as follows: an introduction is provided in Section 1, a literature review of previous studies related to transport manufacturing, trends in energy consumption and carbon, and the related ARIMA-LSTM model is provided in Section 2; the materials and methods are outlined in Section 3; the results and discussion are provided in Section 4; and conclusions are provided in Section 5.

2. Literature Review

The automotive transportation sector plays a significant role in driving economic growth and creating employment opportunities while simultaneously influencing energy consumption [16]. Climate change concerns make it essential to evaluate, quantify, and mitigate greenhouse gas emissions across manufacturing sectors with the greatest substantial energy consumption and GHG emissions [17]. Managing global carbon dioxide emissions aligns with climate change policies, enhancing economic competitiveness and reducing the costs associated with reducing emissions. In 2018, the automotive industry accounted for 29.9% of South Africa's production output and 6.4% of the gross domestic product (GDP) in 2019, while the manufacturing and retail sectors contributed 4% and 2.4%, respectively [1,3]. Automotive component industry operations involve transforming raw materials into finished products. The operations comprise a process that necessitates the energy usage of acidic fluids, scrap generation, noise, and particle pollution, which ultimately lead to environmental contamination [18]. With government-imposed carbon tax regulations on manufacturers, industry stakeholders are obligated to reduce their carbon footprint, energy demand, and electricity consumption. Globally, energy efficiency is acknowledged as pivotal in reducing rising energy consumption. Therefore, the adoption of emerging technologies is crucial and imperative for both present and future energy sustainability. Given its considerable role in transport manufacturing, for electrical energy usage that may result in electric power demand fluctuations, it is mandatory to regulate, estimate, and predict energy consumption to ensure that power delivery remains consistent and of good quality. In this study, statistical and machine learning methods for predicting energy usage based on historical automotive component manufacturing data were used to create systems that can autonomously learn complex patterns in large volumes of data, as described in the following sections.

2.1. Transport Manufacturing: Automotive Component Manufacturing

The transport manufacturing industry grapples with the challenge of increasing production while limiting carbon emissions. The recent increase in vehicle production is directly linked to increased energy costs and environmental impacts [19,20] and has raised global concern over ozone layer depletion, compromised air quality, oxygen depletion, and adverse environmental effects [21]. Economic growth drives future transport sector competitiveness, as presented in the European Commission report [22,23], which stresses the need for targeted innovation and research activities. Meanwhile, research from the United States identified the transport manufacturing sector as the eighth-largest industrial energy consumer, with a surge in energy expenditure of 20% and a nearly 10% increase in electricity purchasing [24]. Achieving transportation ecosystem sustainability is key to addressing issues of fossil fuel dependency and air pollution. The transition from

conventional petroleum-fueled vehicles to electric vehicles (EVs) has been proposed as a prospective solution for mitigating the detrimental effects of GHG emissions, underscoring the significance of product life cycle analyses to manufacturing processes. Cutting-edge technologies such as the Internet of Things (IoT), big data analytics, cloud computing, and cybersecurity have also propelled investment in smart manufacturing [25,26]. In the foreseeable future, transport manufacturing sector technology can improve information visibility, enhance production performance, and result in competitive advantages on the global market. Recent data for the South African automotive component manufacturing sector is limited, while one report has confirmed the presence of 167 vehicle manufacturers and 292 vehicle component manufacturers [27]. The National Cleaner Production Centre (NCPC) has initiated energy management initiatives for up to 13 automotive companies, projecting savings of 75,534,000 kWh of electricity and cost savings of ZAR 41,543,700 (USD 2,957,858), along with an estimated reduction in CO₂ emissions by 72,362 tons [20].

2.2. Trends in South African Automotive Industry Energy Consumption and Carbon Emission Prediction Models

Coal is the main energy resource in South Africa, with manufacturing accounting for 75% of the total energy consumption, resulting in considerable CO₂ emissions [21,22]. Significant electricity users (SEUs) comprise idling machines, compressed air systems, cooling compressors, chillers, ovens and dryers, wet scrubbers, paint shops, and lighting. CO₂ concentration tracking in the atmosphere has revealed that burning fossil fuels has contributed 67% of global CO₂ emissions since 1958, with South Africa playing a substantial role [23]. Energy utilization contributes 1.5% of global carbon emissions, with South Africa being the foremost contributor due to wide-ranging energy usage [24]. South Africa ranked as the 14th-largest emitter of GHGs and relies heavily on coal, with a limited capacity to curb carbon emissions. The task of minimizing emissions falls upon companies, which can implement energy-saving measures that positively impact electricity generation. Almost all industrial activities, including transportation, material extraction, the end-of-life management of used products, and the production of geothermal energy, entail carbon emissions [25]. Ref. [26] presents thermal and energy management software development for a shop floor via an energy-smart production management system in an automotive manufacturing plant. Energy-efficient management prediction remains crucial, and the method established in this study contributes to the sustainability of the latter. The authors of [27] analyzed energy consumption by demonstrating the impact of automotive industry production processes, establishing that the energy consumed for vehicle manufacturing was 62 GJ (41.8 MJ/kg of vehicle). Mining and material production processes accounted for 68% of the overall energy consumption, followed by part production operations at 19% and vehicle assembly at 13%. There exists a gap in energy consumption predictions for continuous energy and resource management, indicating a need to improve the process.

Previous Research on Hybrid ARIMA-LSTM Models

Hybrid models are gaining prominence in data pattern decision-making processes, as they combine the advantages of linear and nonlinear methods to enhance prediction accuracy. Recent trends indicate that hybrid methods are superior to single methods in various applications. Noteworthy studies that precede this work's hybrid ARIMA-LSTM model and support the efficacy of hybrid model predictions are presented in Table 1, which provides a summary of the contributions and limitations of each reviewed article. In the realm of deep learning methods, the hybrid ARIMA-LSTM model proposed in this study aims to enhance the accuracy of short-term and long-term predictions, with the results indicating that this model achieved the highest prediction accuracy. In this study, we introduce a novel hybrid ARIMA-LSTM model tailored for forecasting automotive compo-

nent manufacturing company production data, specifically considering manual operations. This model leverages the advantages of both linearity and nonlinearity, demonstrating superior results compared to individual models. The proposed hybrid ARIMA-LSTM model involves integrating machine learning techniques with optimization algorithms to provide effectiveness by leveraging the strengths and mitigating the weaknesses of individual techniques rather than using single models, ultimately enhancing the prediction accuracy [28,29]. This model aims to increase diversity by adopting the use of real-world time-series data, which are seldom purely linear or nonlinear, necessitating a combination of methods for accurate results. The authors of [30] confirmed that hybrid models such as ARIMA-SVR, LS-SVR, and ARIMA-LSTM outperform single models, with the ARIMA-LSTM model exhibiting the highest prediction accuracy over 6-, 12-, and 24-month scales, making it particularly suitable for long-term forecasting. Furthermore, while ARIMA excels at addressing linear trends, LSTM proves beneficial for capturing the non-stationary components of data and nonlinear patterns. The proposed hybrid model integrates ARIMA for filtering linear trends in time-series data, the residual values of which are then input into the LSTM model for training and predicting residuals for the subsequent year. In this hybrid model, the LSTM model's sole inputs are the residual values derived from the ARIMA model. Previously, applied research resulted in a prediction approach (GA-CNN-LSTM) that combined convolutional neural networks (CNNs) and long-short-term memory (LSTM) networks and was optimized by a genetic algorithm (GA) [30]. Although the accuracy of GA-CNN-LSTM is higher than that of other algorithms during peak time, the overall peak time prediction accuracy is insufficient [31]. An ARIMA-LSTM hybrid model for stock market prediction was also developed; the authors of this study evaluated the performance of ARIMA, LSTM, and ARIMA-LSTM hybrid models for stock prediction using live data. The hybrid model was tested for effectiveness by applying it to five businesses from different industries [32]. An integrated approach to energy efficiency in automotive manufacturing systems was investigated via a quantitative analysis and optimization. The authors presented a simulation-based methodology and developed associated software for modeling thermal and energy management across an automotive manufacturing plant and its application to the effective energy management of the manufacturing systems on a shop floor through an energy-smart production management (e-ProMan) strategy [33]. The authors conducted a complete evaluation of energy consumption in the automotive sector, clarifying the impact of its production processes. For this proposal, the material flow of the cars, from mining to vehicle assembly, was detailed using open data, and the effects on the Japanese vehicle market were analyzed in a case study [34].

Table 1. Related studies preceding the hybrid ARIMA-LSTM model.

Ref.	Description and Contribution	Limitations
[35]	Proposed hybrid model incorporating linear model (ARIMA), nonlinear model (LSTM), and hybrid model (LSTM and ARIMA), demonstrating an improved system performance compared to individual models.	Lack of practical applications in manufacturing and energy consumption.
[36]	Application of ARIMA and LSTM techniques to establish a rolling forecast model, which greatly improves the accuracy and efficiency of demand and inventory forecasting.	Only focuses on the individual models' predictions.
[37]	Novel hybrid model was established that considers the advantages of linearity and nonlinearity, as well as the impact of manual operations, and integrates autoregressive integrated moving average (ARIMA) and long short-term memory (LSTM) models.	Lacks adaptability to predicting energy consumption and carbon emissions.
[38]	Introduced novel hybrid model using long short-term memory (LSTM) and autoregressive integrated moving averages (ARIMAs) for time-series forecasting in live stock market data, outperforming clairvoyant forecasting libraries.	Lack of applications in energy prediction; focused mostly on stock market data.

Table 1. Cont.

Ref.	Description and Contribution	Limitations
[39]	The study aimed to create a monthly sales quantity budget by making use of the previous income in a construction company. To estimate the time series of sales, a linear model, ARIMAs (autoregressive integrated moving averages); a nonlinear model, LSTM (long short-term memory); and a hybrid model (LSTM and ARIMA) built to improve system performance were used and compared.	Focused on predicting sales; lack of practicality and adaptability in energy consumption space.
[40]	Proposed a hybrid random forest (RF) and long short-term memory (LSTM) method based on the complete ensemble empirical mode. Decomposition was achieved with adaptive noise (CEEMDAN) to predict building energy consumption.	Focused on energy consumption, but used a different hybrid technique.

3. Materials and Methods

3.1. Materials

The data utilized in this study to predict future energy usage and CO₂ emissions in transport manufacturing were collected from a tier-two automotive company. Obtained through an energy management training program provided by the National Cleaner Production Centre (NCPC) in South Africa, the dataset spanned three years, encompassing the period from 2016 to 2018. The columns in the dataset include the years, the days on which data were collected, the electricity generated, and the carbon emissions generated during energy consumption. To calculate the proportion of carbon emissions, this study adhered to the guidelines of the Intergovernmental Panel on Climate Change [41], utilizing country-specific emission factors for coal mining. While time-series data can vary in length, it is generally recommended to have at least 20 observations, with some models requiring a minimum of 50 observations for a reliable estimation [42]. In this study, a substantial number of observations, specifically at least 36 per month, were made, offering a representative dataset for energy and carbon data analyses. Assessing the quality of the dataset involves examining its components, namely the trend, seasonality, and noise (residual). Before developing any model, the initial step is to visualize the raw data. Figure 1 provides a visualization of the raw data, clearly indicating the presence of the trend, seasonality, and noise. Therefore, the dataset was deemed suitable for model development.

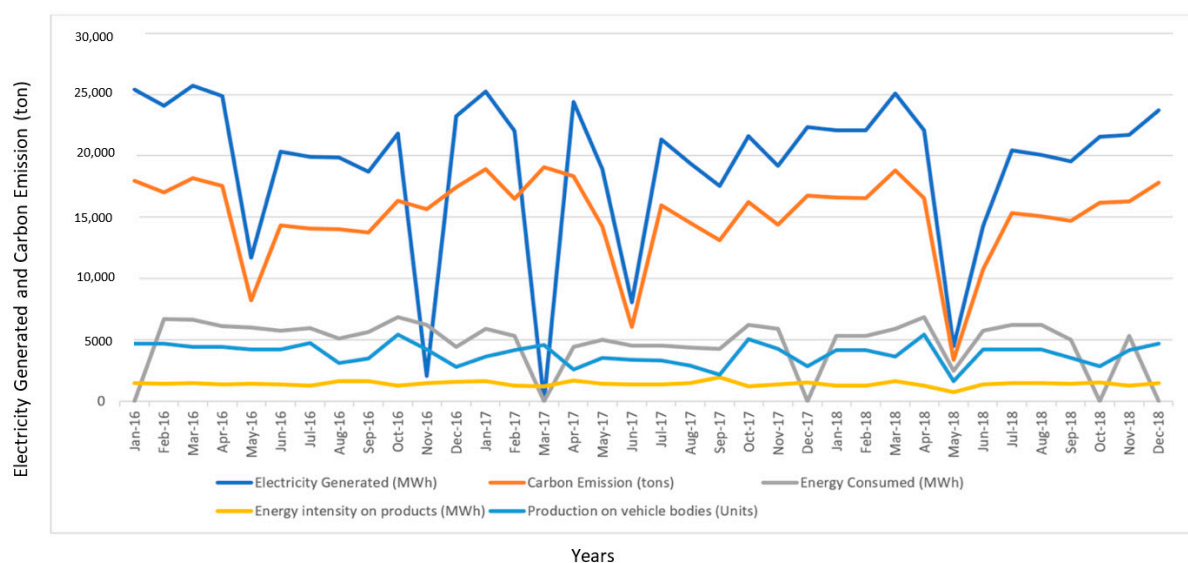


Figure 1. Electricity generated in megawatt hours (MWh), carbon emissions in tons (ton), vehicle bodies produced, energy intensity with expected energy consumption, and savings.

3.2. Methods

A quantitative research method was adopted for the predictive model, encompassing simple linear regression to complex nonlinear neural network algorithms, to ascertain the relationship between electricity generation for vehicle component energy usage and carbon emissions. This methodology involved examining quantifiable data using statistical and computational techniques. The proposed model utilized hybrid ARIMA and ARIMA-LSTM models to predict the energy usage and carbon emissions due to automotive component production. The techniques were selected according to the availability of the dataset. Additionally, consideration was given to the statistical properties introduced by Box and Jenkins [43]. The aim was to achieve accuracy and flexibility across diverse applications, as emphasized by the authors of [44]. The ARIMA model gained recognition among researchers due to its wide-ranging applications in the energy sector and carbon emission studies [45–47]. However, it can only address linear patterns.

3.2.1. Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA combines the autoregressive (AR) and moving average (MA) methods. The hybrid technique is then combined (I) with information from several procedures. The differentiation step is critical to ensuring that the data used in this study can be represented as having stationary features. In 1970, Box and Jenkins proposed the ARIMA model, a time-series analysis method based on stochastic variables that can predict future trends due to their regularities over time. ARIMA modeling and forecasting includes four steps: (1) establishing if a series is non-stationary, meaning that it must satisfy the smoothness test via differential variation; (2) defining the p and q orders using autocorrelation coefficients and partial autocorrelation coefficients; (3) evaluating and testing the model's parameters, and (4) using the chosen parameters to make predictions. Equations (1)–(13) depict the structure of the ARIMA equation.

$$\Delta^d y_t = \theta_0 + \sum_{i=1}^p \varphi_i \Delta^d y_{t-1} - 1 + \varepsilon_t + \sum_{j=1}^q \theta_j \varepsilon_{t-j} \quad (1)$$

The series ε_t represents the residual term at t time, which follows a normal distribution with a mean of 0 and a variance constant σ^2 . The parameters to be estimated are θ_i ($i = 1, 2, \dots, p$) and θ_j ($j = 1, 2, \dots, q$), and the orders are p and q . The aforementioned model can be expressed as ARIMA (p, d, q), where ε_t is an ARIMA (p, q) process and y_t is an ARIMA (p, d, q) process. ARIMA is a linear model, which limits its capacity to describe nonlinear time-series properties. Figure 2 depicts the ARIMA time-series model process framework.

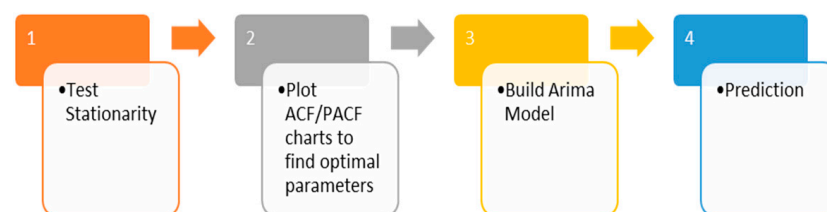


Figure 2. Framework for the time-series model (ARIMA process).

Unit Root Test

A unit root test is a statistical procedure used to determine the stationarity of the series, as follows:

$$(1 - B)y_t = \varepsilon_t; \quad (2)$$

where ϕ is an autoregressive parameter and ε_t is zero mean stationary sequences. If $|\phi| < 1$, the process y_t can be $y_t = (1 - B)^{-1}\varepsilon_t$; thus, the process of y_t is stationary. However, if $\phi = 1$, then y_t corresponds to d (differencing degree) with explosive variance. Therefore, the unit root hypothesis can be formally defined as $H_0: \phi = 1$. There is a procedure for testing H_0 against the alternative hypothesis $H_1: \phi < 1$.

Several strategies have been investigated for stationary testing. This work assessed the two strategies used most frequently in applied research, the Dickey–Fuller (DF) test [48] and the Kwiatkowski–Phillips–Schmidt–Shin test (KPSS) [49], the most appropriate of which was chosen for the investigation. The null hypothesis of the r value is always between -1 and 1 . The negative and positive numbers represent negative and positive associations, respectively. The DF test determines whether an AR model contains a unit root, indicating that the data series is not stationary [48]. Depending on the test type used, the alternative hypothesis might be stationarity or trend stationarity [50]. In the KPSS test, the null hypothesis is that the data are stationary, and we look for evidence that contradicts the null hypothesis. The KPSS test focuses on stationary data, whereas the DF test focuses on non-stationary data. Due to the qualities and type of data available for the study, the DF test was identified as the appropriate unit root test. Dickey–Fuller statistics rely on the least-squares estimations.

$$\hat{\phi} = \frac{\sum_{t=1}^n y_t y_{t-1}}{\sum_{t=1}^n y_{t-1}^2} \quad (3)$$

$$\hat{\sigma}^2 = \frac{\sum_{t=1}^n (y_t - \hat{\phi} y_{t-1})^2}{n - 1} \quad (4)$$

The unit root hypothesis comes from an estimated value ϕ close to one. The Dickey–Fuller t -statistics are then represented by

$$DF = \frac{\hat{\phi} - 1}{\sigma_{\hat{\phi}}} = \frac{\sum_{t=1}^n \varepsilon_t y_{t-1}}{\sqrt{\sum_{t=1}^n y_{t-1}^2}} \quad (5)$$

Optimal parameter correlation includes auto and partial correlation.

Correlation measures the strength of a linear relationship between two variables, and Equation (6) represents the correlation between x and y :

$$r = \frac{\sum (x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum (x_t - \bar{x})^2} \sqrt{\sum (y_t - \bar{y})^2}} \quad (6)$$

The r value is always between -1 and 1 . The negative and positive numbers represent negative and positive associations, respectively. Autocorrelation is defined as a correlation that determines if a time series' values are related to previous values [51]. ACF can also be defined as the correlation between a time series and its lagged variant. When the ACF chart crosses the upper confidence interval for the first time, it returns q [51]. Autocorrelation assesses the link between the lagged values of a time series.

$$r_k = \frac{\sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2} \quad (7)$$

where T is the length of the time series.

A partial autocorrelation function (PACF) computes the correlation between time series using a lagged version of itself after removing previously explained deviations. When the PACF chart reaches the upper confidence interval for the first time, p is calculated [52].

The PACF calculates the correlation between a value in a time series and a prior value after accounting for the correlation due to intervening terms. ARIMA $(0, d, q)$ values are defined as spikes up to lag q that are cut to zero following the ACF values, followed by an exponential decay of the PACF values. Inversely, ARIMA $(p, d, 0)$ values are identified by an exponential decay of the ACF values, reinforced by spikes up to lag p and a cut thereafter to zero of the PACF values.

White noise is defined as any time series with an autocorrelation. The white noise series is expected to have 0% autocorrelation; however, random variations will always exist in real-life circumstances. Approximately 95% of autocorrelation function spikes are expected to fall within the range of $\pm 2/\sqrt{T}$, where T represents the time-series length. If more than 5% of the spikes are outside the boundaries, the time series cannot be considered white noise. AR in the time-series model demonstrates that the present value of a variable is determined by its past and some adjustment variables. The adjustment factors are estimated by comparing the present value to previous values. AR (1), the first-order autoregressive, is the current value based merely on the immediately preceding value, while AR (2) is based on two preceding values. An MA model uses a similar approach to estimate the present value based on current and prior errors, and there can be multiple orders of integration [53]. ARIMA is a time-series model that forecasts stationary time series. The model is mathematically stated as p, d , and q , with the parameters p, d , and q representing the model's structure. This section refers to several books and authors [53,54]. The model is designed by combining autoregressive, AR (p), moving average, MA (q), and differencing degree (d) factors.

$$(B_{bd})\phi_p - yW_t(1 - B_{bd})^d = \delta + \theta_q(B_{bd})a_t \quad (8)$$

$$(B_{bd})\phi_p - yW_t(1 - B_{bd})^d = \delta + \theta_q(B_{bd})a_t \quad (9)$$

$$\theta_q(B_{bd}) = 1 - \theta_1(B_{bd}) - \theta_2B^2 - \dots - \theta_pB_{bd}^{2p} \quad (10)$$

In the above expression, W_t is the TS, B_{bd} is the backward shift operator, d is the order of the schedule difference, and a_t are independent random shocks. The series is a white noise process, and $\phi_p(B_{bd})$ and $\theta_q(B_{bd})$ are polynomials in the B_{bd} of order p and q , respectively. The roots of $\phi_p(B_{bd}) = 0$ and $\theta_q(B_{bd}) = 0$ ought to lie outside the unit circle. Thus, the construction of the model with p is written as follows:

$$W_t = c + \phi_1W_{t-1} + \phi_2W_{t-2} + \dots + \phi_pW_{t-p} + \varepsilon_t \quad (11)$$

where $\varepsilon(t)$ is the white noise, and multiple regression with lagged predictor values is referred to as an AR (p) model. This study utilized a moving average to forecast the historical errors in the regression and the predicted values with the following formula:

$$W_t = c + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \dots + \theta_q\varepsilon_{t-q} \quad (12)$$

where ε_t is the white noise. We designated this as an MA (q) model, a moving average model of order q . Of course, we did not observe the values of ε_t , so it was not a regression in the usual sense. W_t is a weighted moving average of the previous few forecast errors.

Residuals

The main objective of residuals is to check whether the model has adequately captured the information in the data based on Equation (13).

$$\varepsilon_t = y_t - \hat{y}_t \quad (13)$$

The residual of a time-series model is what remains after fitting the model. For most models, the residual is equivalent to the difference between the observed values and the fitted value.

Long Short-Term Memory (LSTM) Model

LSTM models use gates to manage the memorization process, thus avoiding the long-term dependency problem. The initial step in creating an LSTM network is to identify irrelevant information, which is then eliminated from the cell. The sigmoid function, which accepts the output of the last LSTM unit, determines how to identify and reject data. The process of selecting and removing data is defined by the sigmoid function, which uses the output of the preceding LSTM unit (h_{t-1}) @ time $t - 1$, and the current input (x_t) at time t . Furthermore, the sigmoid function determines which parts of the old output to exclude. This gate is termed the forget gate (or f_t), and f_t is a vector with values ranging from 0 to 1, corresponding to each number in the cell state $\tilde{C}_{t-1}$. The “forget gate” determines what information should be discarded. The following formula represents the forget gate:

$$f_t = \sigma(W_f - [h_{t-1}, x_t] + b_f) \quad (14)$$

where σ is the sigmoid function. W_f and b_f are the weight matrix and bias, respectively, of the forget gate (f_t), where f_t is a vector with values ranging from 0 to 1. The output of the last item is represented by (h_{t-1}) at time $t - 1$, and the current input is x_t at time t . The next step is to determine what new information will be stored in the cell state as a result of the new input (x_t) and to update the cell state. This procedure has two unique layers: the sigmoid layer and the tanh layer. The sigmoid layer chooses whether to integrate or discard newly acquired information (0 or 1), whereas the tanh function assigns weights to passed-through input (-1 to 2). Multiplying the two values causes the cell state to change. Later, this additional memory is added to the previous memory input gate, i_t , resulting in unit $\tilde{C}_t$, represented by Equations (15) and (16):

$$i_t = \sigma(W_i - [h_{t-1}, x_t] + b_i) \quad (15)$$

$$\tilde{C}_t = \tanh(W_c - [h_{t-1}, x_t] + b_c) \quad (16)$$

where $\tilde{C}_{t-1}$ and $\tilde{C}_t$ are the cell states at time $t - 1$ and t , while W and b represent the cell state's weight matrix and bias, respectively. The next step is to identify what new information will be saved in the cell state. The input gate layer determines which values will be changed, as illustrated by Equation (17).

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (17)$$

The output decision will be dependent on the cell's state, but it will be filtered from the original output, as shown in Equation (18). In the final stage, the output values (h_t) are derived from the output cell state (O_t), but they are filtered. First, a sigmoid layer determines which elements of the cell state are output. The output of the sigmoid gate (O_t) is multiplied by the new values formed by the tanh layer from the cell state (C_t), with a value ranging from -1 to 1 . This is represented by the output gate, Equations (18) and (19), and the simplified version of LSTM given in Figure 3.

$$O_t = \sigma(W_o - [h_{t-1}, x_t] + b_o) \quad (18)$$

$$h_t = O_t * \tanh(C_t) \quad (19)$$

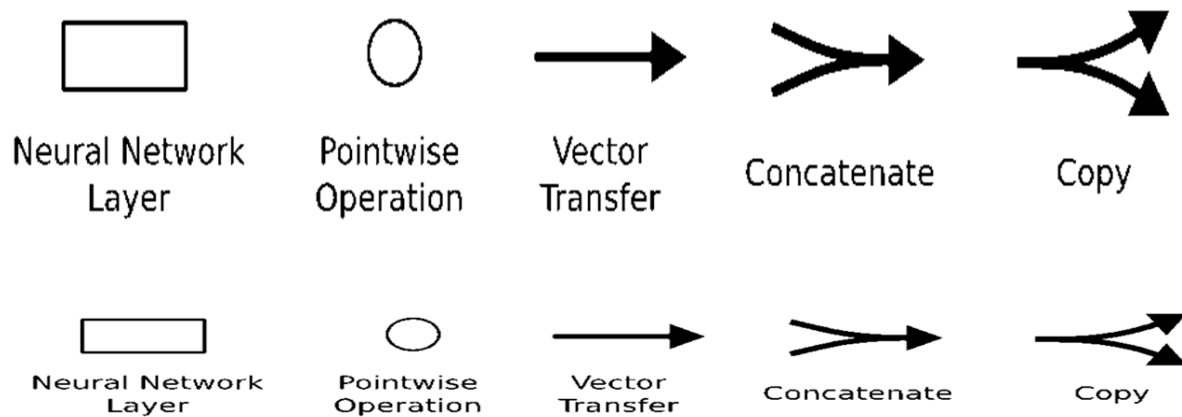


Figure 3. Cellular structure of LSTM.

3.2.2. ARIMA-LSTM Model

Based on the aforementioned review, it is obvious that ARIMA outperforms in terms of linear predictions, but LSTM outperforms in terms of time-series predictions. ARIMA and LSTM may be capable of more accurate prediction tasks. This study examined carbon emission data and highlighted its time-series features. To optimize the utilization of carbon emission data, we assumed that it contained both linear and nonlinear information. This study employed the inverse error combination method to detect linear and nonlinear information in carbon emission time-series data and improve the prediction accuracy by combining the ARIMA and LSTM models. This study provides a weighted combination (Equations (20) and (21)) to improve the prediction accuracy.

$$f_1 = \omega_1 f_{1t} + \omega_2 f_{2t}, \quad t = 1, 2, \dots, n \quad (20)$$

$$\omega_1 = \frac{\lambda_2}{\lambda_1 + \lambda_2} \quad (21)$$

$$\omega_2 = \frac{\lambda_{12}}{\lambda_1 + \lambda_2} \quad (22)$$

In Equation (20), f_{1t} represents the prediction value obtained via LSTM or ARIMA, ω_1 is the weight coefficient, and λ_1 and λ_2 are the LSTM and ARIMA prediction errors. This method assigns higher weight factors to models with fewer errors to reduce the total model error and prediction value error, thus increasing the prediction accuracy. ARIMA filters linear trends in time-series data, and residual values are fed into an LSTM model trained to recognize patterns and forecast residuals for the following five years.

Validating the ARIMA-LSTM Model's Predictive Evaluation Indicator

The reliability of trained models was assessed using a time-series prediction performance assessment, which revealed effective ARIMA and ARIMA-LSTM hybrid models. Figure 4 shows the steps taken for training and testing the data. The root mean square error (RMSE) provided in Equation (23), which is the normalized difference between the observed and anticipated values, is a method used to measure and predict errors in quantitative data. The non-absolute magnitude of the mistake iteration is lowered from step to step by heuristically applying the projected evaluation indicators.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_1(t) - y_t(t))^2} \quad (23)$$

where y_t is the actual value, f_t is the predicted value, and k is the sample size and square error. In addition, in the hybrid formulation proposed here, the residuals from the rolling LSTM model are analyzed for further optimization.

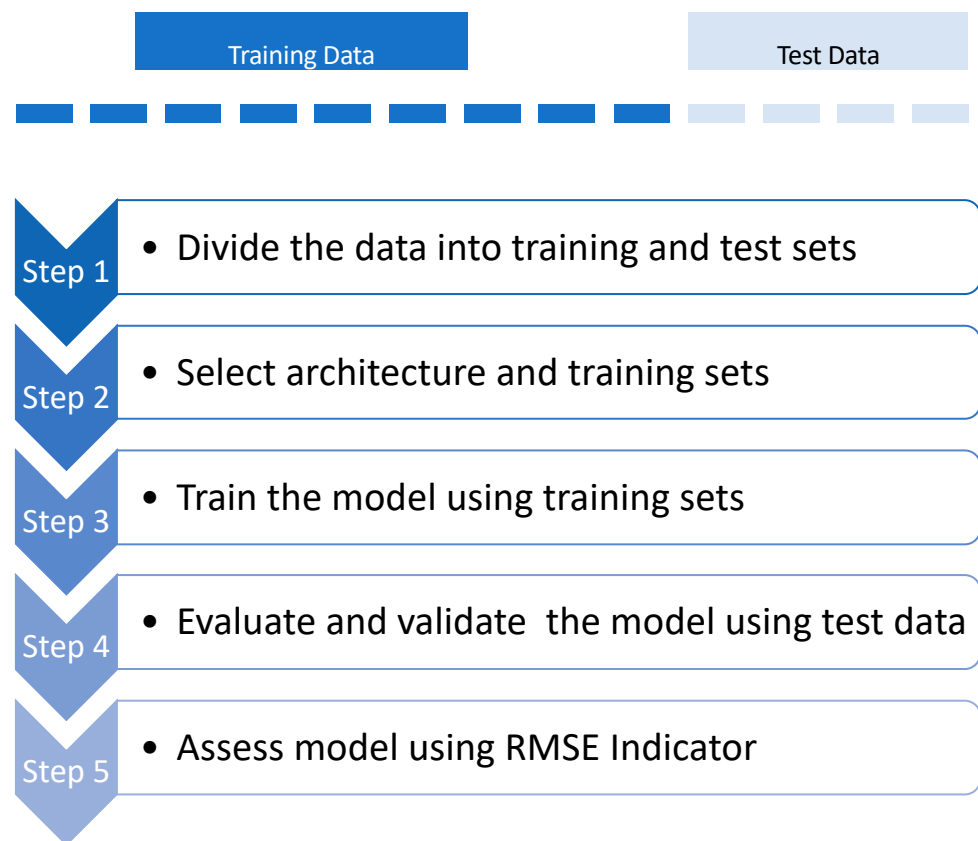


Figure 4. Process of training and testing the data.

ARIMA-LSTM Predictive Indicators

The reliability of trained models was evaluated using a time-series prediction performance assessment, which also revealed the effective ARIMA and ARIMA-LSTM hybrid model provided by the RMSE in Equation (24).

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - f_t)^2} \quad (24)$$

The hybrid model findings, when compared to those produced using the individual models, demonstrate the possibility of general variance or error reduction, even if they are unrelated. As a result, hybrid models are regarded as the most effective for generating predictions. Figure 5 illustrates the framework for ARIMA-LSTM modeling.

3.3. Computation of Model: Python Programming

Statistical and machine learning predictions necessitate extensive computation. This study used Python 3: version 3.10 to create analytical software. Python is an open-source programming language used for artificial intelligence, natural language processing, and machine and deep learning [45]. Artificial intelligence efforts differ from regular software projects in terms of the technology stack, the skills necessary for AI projects, and the need for substantial research. Python meets stability and adaptability requirements from development to deployment. Table 2 shows the pseudocode for the hybrid model.

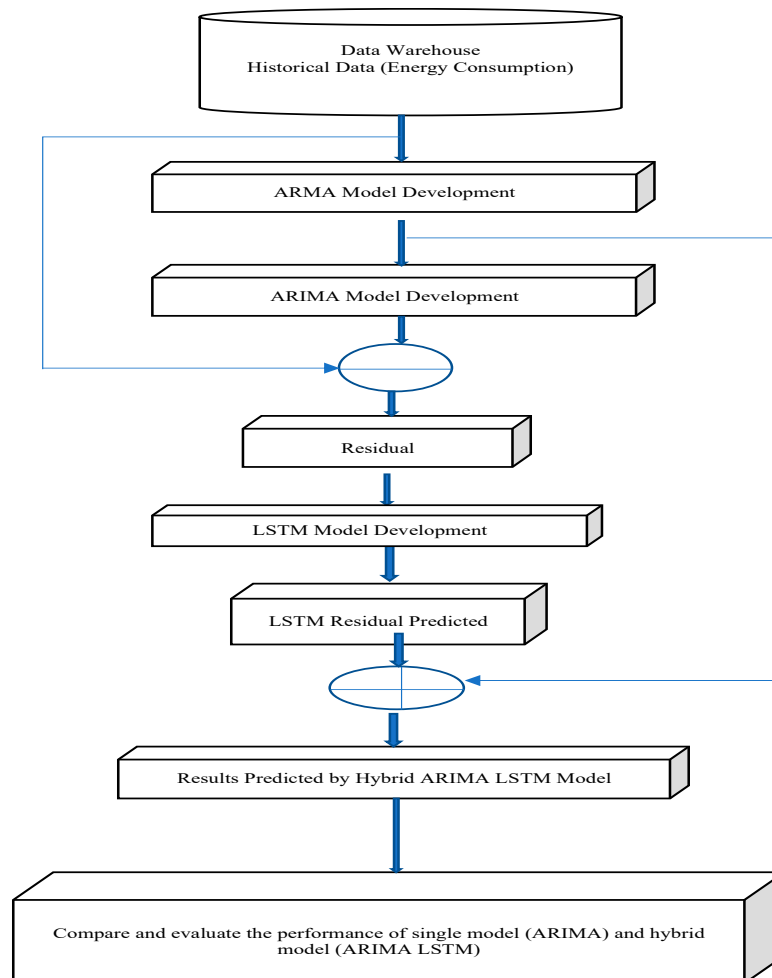


Figure 5. Framework for energy and carbon efficiency hybrid model (ARIMA-LSTM).

Table 2. Hybrid IPO and pseudocode.

Input	Processing	Output
1. Energy_test_data.csv: CSV File Containing the Following: - Date: dates of observations. - Electricity generated: electricity generation data (MWh). 2. Hyperparameters: - ARIMA: ($p = 1, d = 0, q = 1$), Seasonal: ($P = 3, D = 1, Q = 3, m = 12$). - LSTM: $n_input = 12, n_features = 1, epochs = 20, 40, 60, 80, 100$.	1. Data Preprocessing: - Load the CSV file into a Pandas Data Frame. - Convert the date to date-time format and set it as the index. - Visualize the data using line plots. 2. Data Analysis: - Plot time-series data for insights. - Decompose the series into seasonal, trend, and residual components. 3. ARIMA Modeling: - Split the data into training and testing sets. - Use <code>auto_arima</code> to determine the optimal parameters. - Fit a SARIMAX model with the identified parameters. - Generate ARIMA predictions on test data. - Compute errors (RMSE, MSE) for ARIMA predictions. 4. LSTM Modeling: - Normalize the data using <code>MinMaxScaler</code> . - Generate sequences with a time-series generator. - Build and train an LSTM model. - Generate LSTM predictions on test data. 5. Hybrid: - Build and train an ARIMA-LSTM model. - Plot actual values against ARIMA-LSTM predictions.	1. Visualization of the Following: - Original and decomposed time-series components. - Model predictions (ARIMA and LSTM) vs. actual values. - Training loss curve for LSTM. 2. Model Evaluation Metrics: - ARIMA: RMSE, MSE, and comparison with the mean of the series. 3. Forecasted Values: - Predictions from ARIMA and LSTM, stored in <code>test_data</code> .

4. Results and Discussion

The Dickey–Fuller test, a statistical test for stationarity, was used in this study. The null hypothesis stated that the time series (TS) was not stationary in this case. The test findings are reported in two formats: test statistics and crucial values at various confidence levels. If the “test statistic” is smaller than the “critical value”, the null hypothesis that

the TS is not stationary can be rejected. The Dickey–Fuller test was performed at several levels of data processing, including on raw data, post-estimation with trend elimination, during trend and seasonality elimination, and on residuals, as shown in Table 3. The rolling statistic test gives a visual depiction, whereas the Dickey–Fuller test produces numerical values for the determination of data stationarity. Figure 6 a,b depict the idea that time-series decomposition facilitates the identification of data exhibiting variations in the mean or variance; the electricity generated revealed both upward and downward patterns. Nonetheless, the trend in electricity generation is analogous, and the data likewise indicated seasonal fluctuations. A consistent decline in electricity was produced annually during the fifth month.

Table 3. Dickey–Fuller test results for stationarity post-eliminating trend and seasonality.

Description	Original Data	Post-Estimating and Eliminating Trends	Post-Eliminating Trend and Seasonality	Residual Results
Test statistic	−3.602352	−9.397422	−7.793783	−7.590148
<i>p</i> -value	0.005716	6.31922	7.815122	2.544113
Number of lags used	6	1.5	8	1.300000
Number of observations used	1086.00000	1.066	1.084	7.040000
Critical value (1%)	−3.436386	−3.436499	−3.46397	−3.439673
Critical value (5%)	−2.864205	−2.864255	−2.86421	−2.865654
Critical value (10%)	−2.568189	−2.568216	−2.568961	−2.568961

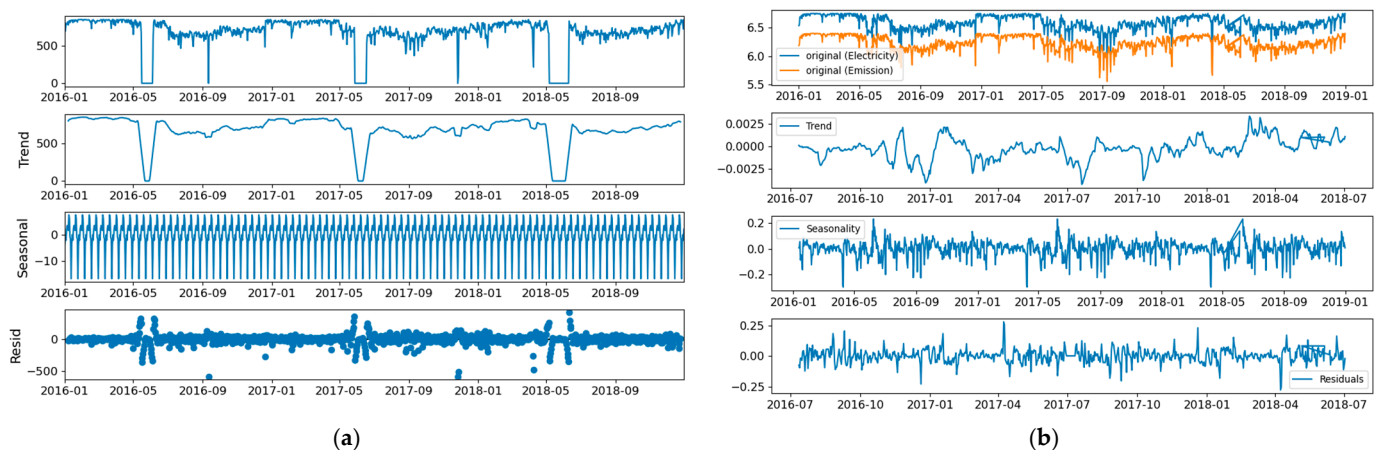


Figure 6. (a) Time-series electricity-generated data decomposition. (b) Decomposition, original data, trends, seasonality, and residual models (ARIMA).

In conjunction with the Dickey–Fuller test results reported in Table 3, the test statistic (−7.7) was compared to the 10% critical value (2.5), indicating that the time series was stationary with 90% confidence. Notably, the series showed less volatility in the magnitudes of its mean and standard deviation. Furthermore, the Dickey–Fuller test for residuals yielded a test statistic of −7.50, which is much lower than the 1% critical value (−3.4). This validates the residuals’ stationarity. As a result, based on these findings, the study continued with the forecasting process.

Hyperparameters (HPs) are parameters that cannot be learned directly using the primary learning algorithm (for example, gradient descent), but that have an impact on the learning process and prediction performance. Overfitting is a major problem that develops when training a neural network using sample data [42]. In machine learning, the epochs used for training should be kept to a minimum because they are mostly specific to the sample data. The data are interpreted using the loss value for all training data after

each epoch. Because the training process is designed to minimize this, the optimization approach chooses the lowest attainable value, as seen in Figure 7.

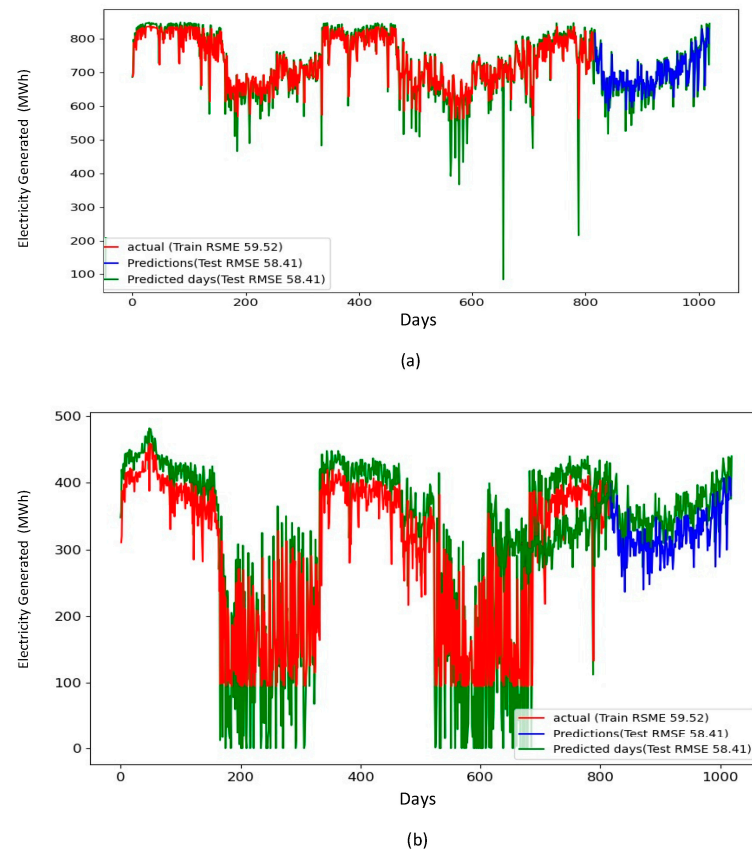


Figure 7. (a) Model evaluation and validation; (b) RMSE for actual training data and predicted test data.

As shown in Figure 8, the training losses for each epoch are as follows: 0.087 for epoch 40, 0.080 for epoch 60, 0.074 for epoch 80, and 0.072 for epoch 100. In this particular example, epoch 100 offered the most favorable outcome; hence, 100 epochs are preferable for the predictive analysis.

A comparison of the relative percentage predictions of the proposed ARIMA-LSTM model and other models in the literature regarding electrical energy consumption is presented in Table 4.

Table 4. Relative percentage prediction performance of ARIMA-LSTM: model comparison.

Authors	ARIMA (RMSE)	ARIMA-LSTM (RMSE)	Relative Percentage Prediction (%)
Authors of this work	448.89	58.41	13.01
Pierre et al., 2023 [55]	49.90	7.35	14.72
Trisya et al., 2024 [56]	11.4183	7.659	67.07

The compared values of the authors' work in Table 4 show relative percentage prediction differences of 1.62 and 54.06 with the results obtained by the authors of [54] and [55], respectively. The significance of the proposed work is demonstrated by the performance comparison of the ARIMA-LSTM and ARIMA models for energy consumption analyses in these studies. Future studies may also consider the energy storage global economical and optimal model proposed by the authors of [56].

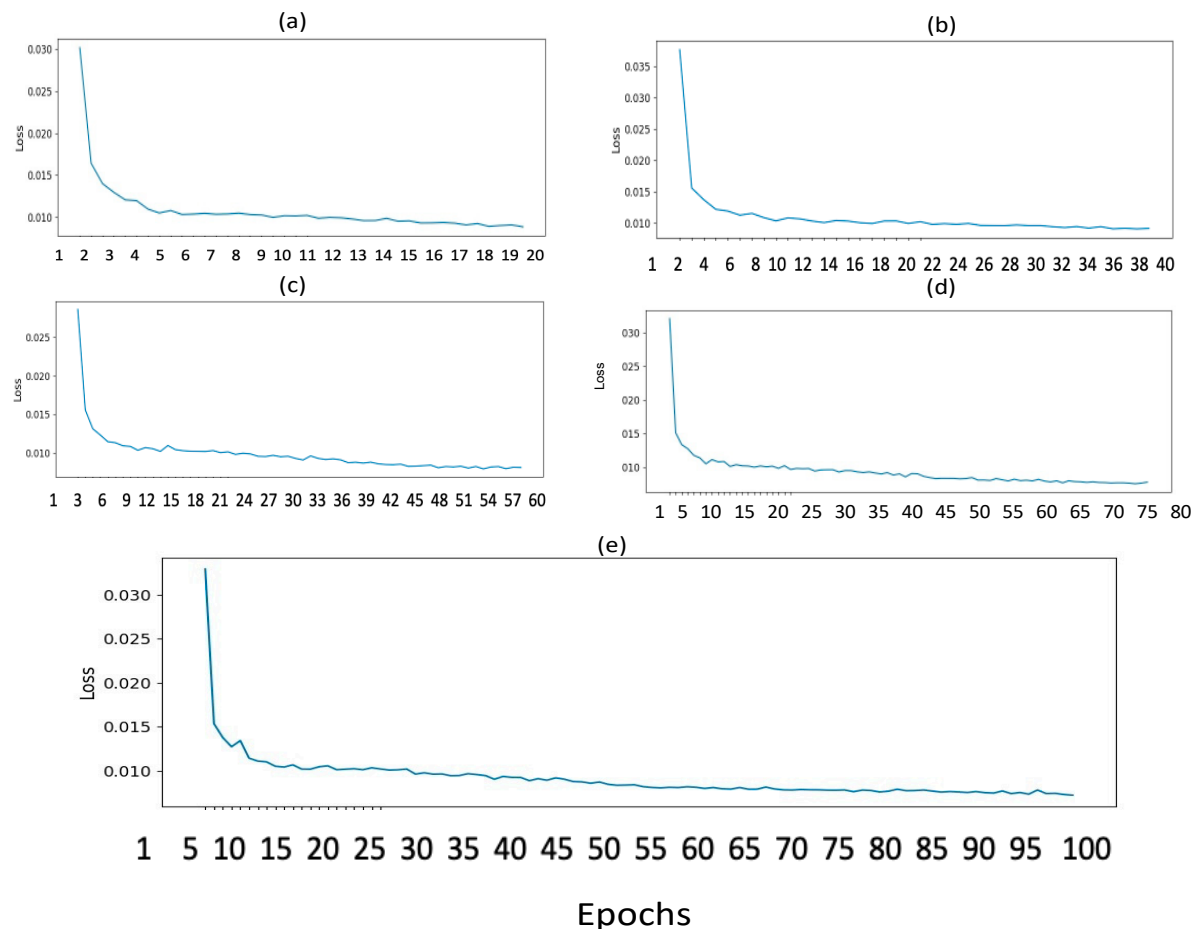


Figure 8. ARIMA-LSTM prediction analysis: hyperparameter epochs. (a) epoch 20; (b) epoch 40; (c) epoch 60; (d) epoch 80; (e) epoch 100.

5. Conclusions

This study presents a hybrid ARIMA-LSTM prediction model that demonstrates a superior performance in predicting trend variability and influencing energy consumption in the automotive component manufacturing sector. This method demonstrates the ability to capture linear and nonlinear patterns in time-series data; ARIMA captures linear features, and LSTM captures long-term dependencies in the data. This information will support decision makers in energy management and decarbonization planning. The objective was to construct two models and test which model fit best for prediction using the configuration that yielded the lowest root mean square error. Demand intelligence is essential for identifying flaws in previous data and accurately predicting CO₂ levels to meet climate change targets. The hybrid ARIMA-LSTM prediction model approach aims to minimize CO₂ emissions and enhance energy consumption to support climate science research. Future studies will integrate energy and carbon emission predictions into a data-monitoring device compatible with web and mobile apps for the future transportation manufacturing industry. The root mean square error (RMSE) for the ARIMA model is 448.89, whereas the actual and predicted values for the ARIMA-LSTM model are 59.52 and 58.41, respectively. The interdependence of variables resulted in a 29% improvement in the total energy intensity spent on vehicle body part products, a 7.22% reduction in cumulative energy savings, and a 16.25% increase in energy efficiency. The training losses for epochs 40, 60, 80, and 100 were 0.087, 0.080, 0.074, and 0.072, respectively.

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