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Deep learning hybrid models for effective supply chain risk management: mitigating uncertainty while enhancing demand prediction

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Abstract: In today's rapidly evolving business landscape, effective supply chain management (SCM) is crucial for achieving success. Accurately predicting product demand is a significant challenge for companies, impacting customer satisfaction, inventory optimization, cost reduction, and operational efficiency. This study focuses on demand forecasting within intelligent supply chains (SCs) and supply chain risk management (SCRM), aiming to enhance overall SC efficiency and mitigate risks, highlighting the use of deep learning hybrid and singles models to address SCRM challenges, specifically in mitigating uncertainty and improving demand prediction accuracy. Our research paper investigates predictive modeling techniques for demand forecasting within the automotive sector. Specifically, we assess the effectiveness of Seasonal Autoregressive Integrated Moving Average (SARIMA), Long Short-Term Memory (LSTM), Artificial Neural Network (ANN), Recurrent Neural Network (RNN), and a hybrid RNN-ANN model with Gradient Boosting (GB). Through meticulous analysis and evaluation, we demonstrate the superior predictive accuracy of the hybrid model compared to individual models. The results indicate consistent outperformance of the hybrid model, as evidenced by lower Mean Absolute Error (MAE) and Mean Squared Error (MSE) values across electric and thermal product categories. This research aims to provide valuable insights and practical tools for businesses to refine their demand prediction processes. By addressing demand uncertainty, organizations can streamline their SCs, minimize costs, and establish a responsive and adaptable framework for sustainable growth.

1 Introduction

In today's fiercely competitive manufacturing landscape, companies are increasingly turning to demand-driven SCs to navigate the complexities of fluctuating customer demands. This shift underscores a fundamental change in market dynamics, where customers wield unprecedented influence by specifying their desired products and delivery schedules to suppliers.

Effective demand forecasting is paramount in this environment, as it enables companies to optimize resource utilization across production, inventory management, and transportation. Accurate predictions facilitate the alignment of production quantities with anticipated demand, resulting in cost savings and the maintenance of optimal inventory levels while minimizing excess stock. This optimization not only fosters efficient SCM but also ensures the timely fulfillment of customer demands.However, inaccurate predictions can trigger the bullwhip effect [1] a phenomenon in SCM where minor changes in consumer demand lead to magnified fluctuations as they propagate upstream. This distortion of information among wholesalers, manufacturers, and suppliers can result in substantial variability within the SC, leading to excess inventory, wastage, operational inefficiency, and diminished profits.

Moreover, as traditional SC undergoes development, technology is becoming increasingly ingrained. Many SCs have already incorporated advanced technological components like digitalization, networking, and automation. This is especially noticeable in the automotive SC, where the adoption of new technology, particularly deep learning (DL), is a direct consequence of integrating cutting-edge scientific advancements and technological innovations to modernize traditional practices. The integration of artificial intelligence (AI) technologies, including machine learning (ML) and DL, has played a significant role in the intelligent evolution of the conventional SC.

Researchers have produced a plethora of work in the field of forecasting, proposing numerous methods and techniques mainly with ML and DL methodologies, which have showcased their effectiveness in handling vast amounts of data with numerous dimensions, revealing latent patterns crucial for decision-making and prediction [2]. These methodologies have displayed remarkable performance across various domains, such as demand forecasting and price prediction, often surpassing traditional statistical approaches [3-4]. Notably, DL models like Convolutional Neural Networks (CNNs), ANN and RNNs stand out for their capacity to automatically extract meaningful features from data decreases the need for manual feature engineering.

The application of DL extends to various SC forecasting tasks, covering domains like production forecasting, pricing forecasting, and demand forecasting.For instance, [5] explored the multi-step ahead prediction of coal prices by employing a hybrid DL model. [6] investigated optimal pricing challenges faced by members of the automotive SC, emphasizing the pivotal role of prediction as the foundation for pricing decisions. [7] utilized statistical and econometric theories and methodologies to predict future demand for new energy vehicles within the automotive SC domain. These studies demonstrate the superiority of these models over traditional statistical methods, which, being fundamentally linear, struggle to effectively handle uncertainty and demand fluctuations. While single models have proven effective in various fields, there is limited adoption of hybrid models in demand forecasting, indicating a potential area for further exploration. Furthermore, there is a prevailing tendency to rely on single models rather than adopt combined hybrid models.

This study is grounded in the context of intelligent SCs, acknowledging the crucial role of demand forecasting in SCM, the incorporation of demand forecasting into the SCRM context offers several noteworthy contributions:

Risk anticipation: The precision of demand forecasting aids in anticipating potential risks associated with fluctuations in demand. By comprehending demand patterns, SC managers can proactively identify and prepare for potential disruptions, enhancing risk anticipation.

Inventory management: Accurate demand forecasting supports the optimization of inventory levels, leading to reduced holding costs, and mitigates the risks of stockouts or excess inventory.

Supply chain resilience: Recognizing uncertainties in demand empowers SC managers to design systems that are more resilient and adaptable to various scenarios.

Supplier collaboration: Demand forecasting fosters improved collaboration with suppliers. Understanding future demand patterns enables suppliers to align their production schedules and capacities with anticipated requirements, thereby reducing the risk of disruptions in the SC.

Resource allocation: Accurate demand forecasting guides decisions related to resource allocation, encompassing labor, transportation, and production capacities. Aligning resources with forecasted demand aids in the effective management of operational risks.

Data-driven decision-making: The utilization of AI and DL for demand forecasting facilitates more precise predictions, supporting data-driven decision-making in the realm of SCRM.

Scenario planning: Demand forecasting enables the creation of diverse demand scenarios. SC managers can leverage scenario planning to assess the potential impact of various demand-related risks, allowing for the development of robust contingency plans.

In essence, this research acknowledges the integral role of demand forecasting in SCRM. By incorporating these perspectives, the study seeks to demonstrate a comprehensive understanding of how effectively managing demand uncertainties contributes to the overall resilience and risk mitigation of intelligent SCs through DL techniques. It proposes an innovative approach that combines single and hybrid models, including SARIMA, LSTM, ANN, RNN, and GB, with the goal of improving the accuracy of customer demand prediction.

The rest of this document is structured as follows: the subsequent section comprises an in-depth examination of existing literature, the third section presents the research methods and the procedural details employed as the foundation for this paper, the fourth section scrutinizes and deliberates on the experimental findings, analysis and discussions,the fifth and final section encapsulates the conclusions drawn in this paper, along with future prospects for the field.

2 Literature review

Demand forecasting involves predicting future market demand, and the accuracy of this forecast directly affects a company's production plan, inventory management [8] and customer satisfaction [9]. It can be classified into two primary types: qualitative forecasting and quantitative forecasting. Qualitative forecasting depends on subjective judgments and expert opinions, using methods like group discussions and the Delphi method for assessing and predicting product output. On the other hand, quantitative forecasting employs data to establish mathematical models for prediction.Presently, statistical methods such as time series models and grey forecasting models, along with advanced algorithms like ANNs and support vector machines, are commonly used in demand forecasting.

In recent times, due to the swift progress of AI, there have been numerous proposals for advanced demand prediction methods employing DL models to enhance the efficiency of SCM. AI holds the potential to enhance various aspects of SCM, ranging from order forecasting to delivery management. The utilization of DL techniques facilitates the rapid analysis of extensive datasets and the construction of effective prediction models. Given these advantages, diverse industries, including but not limited to fashion [10,11] retail [12-21], tourism [22], electricity [23-26], among others [27,28], have endeavored to enhance their SCM through the incorporation of AI techniques.

The subjective nature of qualitative forecasting often results in being influenced by the personal biases of the researcher, leading researchers to frequently opt for quantitative forecasting methods. For instance, certain scholars utilized the autoregressive integrated moving average (ARIMA) model to predict the recall volume of cars for companies engaged in auto importing [29]. In cases where time series exhibit significant fluctuations and the environment is less stable, traditional statistical forecasting methods may yield suboptimal results. Consequently, an increasing number of researchers have introduced DL methods to enhance predictive accuracy. Some researchers have recommended using the ARIMA model or multi-layer perceptron (MLP) for forecasting flood flows [30,31]. For instance, [32] utilized an ANN model to forecast car sales in the Turkish region. In another context, [33] they presented a short-term prediction system utilizing bidirectional long short-term memory (Bi-LSTM) for smart power grids. Additionally, [34] utilized a RNN to forecast the quantity of damaged car parts. In the pursuit of improved forecasting precision, demand forecast models are increasingly transitioning from single-model prediction to combination-model prediction. Combination models primarily involve the integration of traditional forecasting methods [35] involves combining traditional methods or econometric forecasting with DL forecasting methods [36] and combination models founded on multiple DL single models [37]. Scholars have significantly improved the accuracy of combined forecasting models by preserving and integrating the strengths of individual models.Some scholars predict the demand for spare automotive parts using an enhanced LSTM model, and the accuracy of predictions can be increased by refining the prediction algorithm within DL [38]. Other studies employed ANNs and MLP integrated models for air pollution prediction [39,40]. When forecasting the traffic flow of port vessels, [41] applied the SARIMA-BP model, highlighting that the joint utilization of both models yields greater optimality compared to relying solely on the SARIMA model, especially in handling more volatile data. Certain researchers choose to integrate DL methods to improve the accuracy of forecasting models. For instance, [42] Predicted China's industrial carbon peak using the BP-LSTM model, illustrating that forecasting with two deep learning models is significantly more accurate than relying on a single deep learning model. In essence, employing a combined forecasting model allows for the integration of diverse model advantages, effectively addressing the challenge of unstable time series, enhancing prediction speed, and reducing errors.

Currently, there is a limited amount of research on demand prediction, highlighting the urgent need for greater attention and exploration in this area. Accurate forecasting of product demand is essential for guiding decision-making in subsequent production, transportation, storage, and sales operations within the intelligent SC. The accuracy of demand forecasting is a pivotal factor supporting automotive companies in expanding their market shares and boosting profits. Limitations exist within the automotive SC, although they have been less thoroughly investigated. However, there is a pressing need for more research in this specific type of SC, given its complexity and extensive nature.

Hence, this research introduces a combination of single and hybrid models, utilizing customer demand data for a products purchased by an OEM. The model aims to forecast future demand for these specific products, considering the volatility inherent in customer demand data.

3 Methodology

In our study, we are tasked with the complex challenge of predicting customer demand, a critical aspect of operations for our company in the automotive sector. To address this challenge comprehensively, we carefully selected a range of individual and combined models and organized the process following the methodology outlined in Figure 5.

3.1 Exploratory data analysis and preprocessing

Our study leverages a comprehensive dataset spanning from 2019 to 2023, comprising 60 columns rich with information encompassing customer profiles, project details, product specifications, operational metrics such as hours, pricing data, and vehicle attributes including age, brand, and model. To ensure data quality and consistency, we embarked on a rigorous data preprocessing and analysing phase. This involves integrating exploratory data analysis (EDA) into our process for gaining a deeper understanding of the underlying data characteristics. Through EDA, we conducted an initial exploration of the dataset, identifying trends, patterns, and seasonality that informed subsequent preprocessing and feature engineering steps. Figure 1, illustrate key insights gleaned from our EDA process, providing visual representations of the data distribution and relationships.

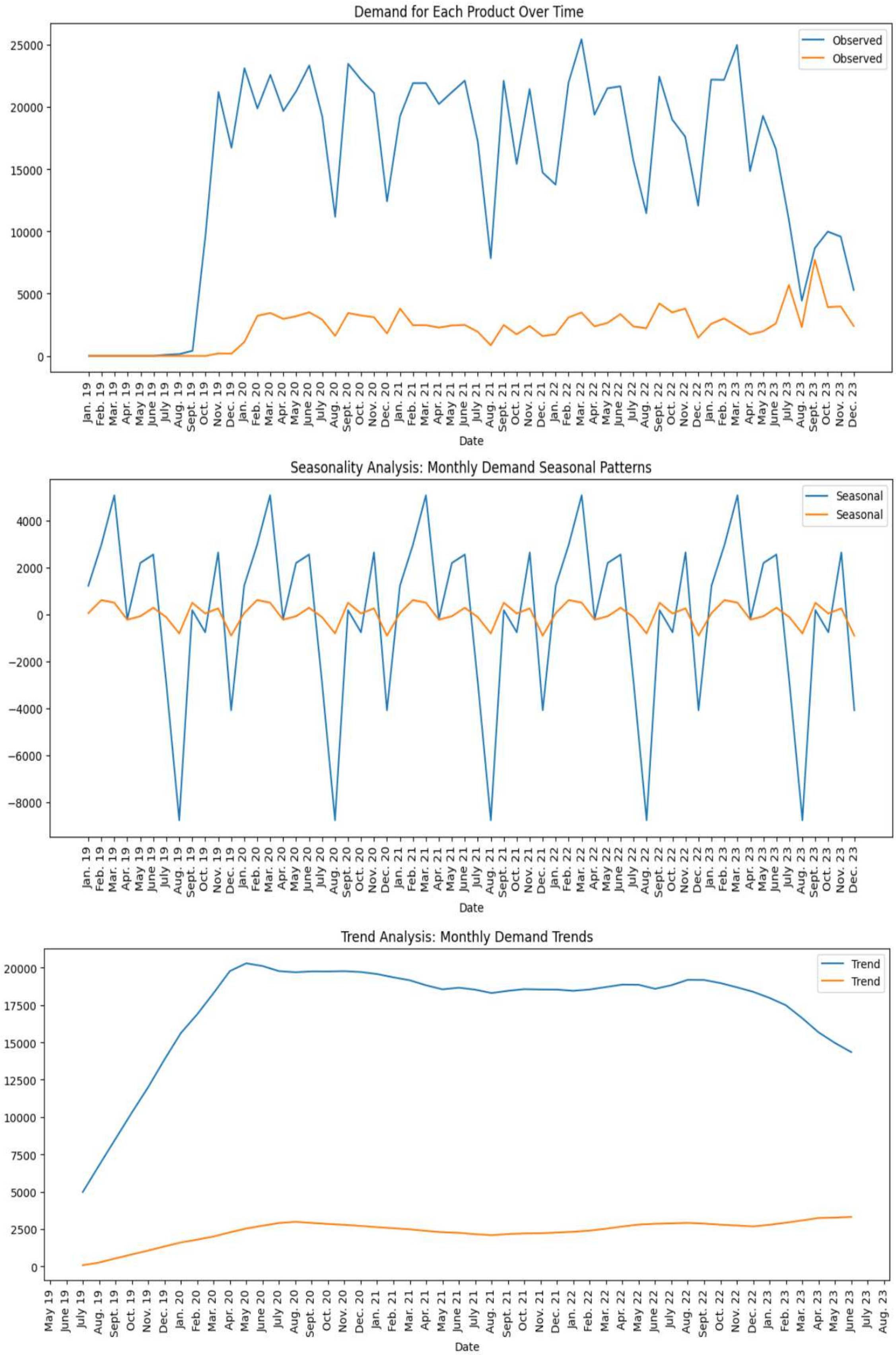


Figure 1 Data distribution, trend, seasonality

Some insightful observations from the trend were identified, such as the initial increase indicating a period of growth in demand, subsequent stabilization suggesting relatively constant demand, a slight smooth decrease indicating a gradual decline in demand over time, and significant fluctuations in demand occurring at regular intervals. This variability is mainly related to customer preferences, potentially influenced by seasonal factors such as holidays, sales trends, or other external influences. In seasonal decomposition, negative values represent deviations from the average seasonal pattern observed in the data, indicating periods where the actual demand is lower than expected based on typical seasonal behavior. These deviations present opportunities for improvement. By identifying periods of lower demand, businesses can explore strategies to stimulate demand during off-peak seasons.By analyzing the trend and seasonality components of the dataset, we are equipped to understand the underlying patterns in the demand data and make informed decisions to optimize operations.

3.2 Feature engineering

In the feature engineering step, we focus on extracting relevant features from the data to enhance the predictive power of our models. This involves the creation of both temporal and non-temporal features.For temporal features, we leverage the time-related aspects of the data, to capture trends, seasonality, and periodic patterns. Common temporal features include month, and year. These features provide valuable insights into the temporal dynamics of the data and can help improve the accuracy of our predictions. In addition to temporal features, we also engineer non-temporal features that capture other aspects of the data unrelated to time. These features include customer profiles, project details, product specifications. By encoding and transforming these features appropriately, we aim to capture meaningful information that can further enhance the predictive performance of our models.

3.3 Models architecture design

We commence our modeling approach by adopting SARIMA model, a classical time series forecasting model renowned for its ability to capture seasonal terms to capture periodic patterns in demand data, autoregressive terms for serial correlation, differencing to remove trends, and moving average terms for residual errors. By leveraging these components, SARIMA stands poised to offer insights into the nuanced temporal variations of customer demand, discerning seasonality, trends, and fluctuations in time-series data. Additionally, SARIMA's capability to combine ARIMA components with seasonal components enables the model to capture both non-seasonal and seasonal patterns effectively as in equation (1).

$$Y_t = \Phi_p\, Y_{t-p} + \Theta_q \varepsilon_{t-q} + \phi_P Y_{t-P} + \Theta_Q \varepsilon_{t-Q} + \mu + \varepsilon_t \quad (1)$$

Where : Y_t represents the observed value at time t. Φ_p and Θ_q are autoregressive and moving average parametres for non-seasonal components ,respectively. Y_{t-P} and ε_{t-Q} are lagged values of the time series and residuals from previous observations,respectively. P and Q represent the seasonal periods. μ is the mean of the time series. ε_t Is white noise.

Building upon the foundation laid by SARIMA, we incorporate the LSTM model,as it is structure is well-suited for capturing long-term dependencies and complex temporal relationships in sequential data as in equations (2),(3),(4),(5),(6),(7), Figure 2. Its inclusion enhances our model's capacity to capture intricate patterns in customer demand.

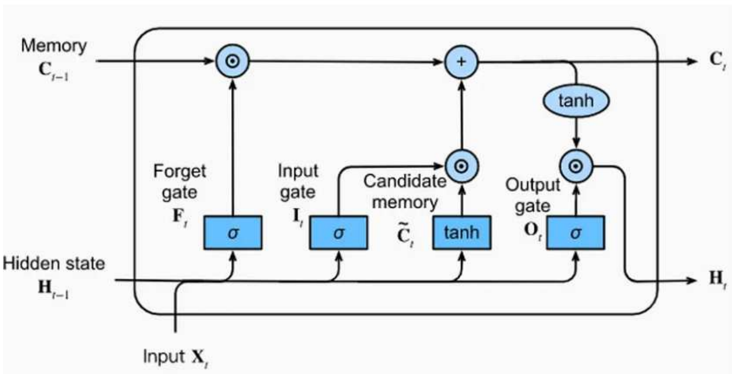


Figure 2 Cell structure of the LSTM

$$i_t = \sigma\,(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i \quad (2)$$

$$f_t = \sigma\,(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f \quad (3)$$

$$g_t = tanh\,(W_{xg}x_t + W_{hg}h_{t-1} + b_g \quad (4)$$

$$o_t = \sigma\,(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o \quad (5)$$

$$c_t = f_t * c_{t-1} + i_t * g_t \quad (6)$$

$$h_t = o_t * tanh\,(c_t) \quad (7)$$

Where: x_t is the input at time step t , h_{t-1} is the previous hidden state, c_{t-1} is the previous cell state (memory), i_t, f_t, g_t, and o_t are the input, forget, cell, and output gates, respectively. σ is the sigmoid activation function. W and b are the weight matrices and bias vectors for each gate.

In addition to SARIMA and LSTM, we consider the adoption of an ANN and RNN. These models offer versatility and scalability, allowing us to explore different facets of demand prediction and complement the strengths of SARIMA and LSTM.We deploy the ANN model with its capacity to learn intricate mappings between input features and output predictions as in equation (8), Figure 3, as well as RNN model is ability to analyze sequences of data by retaining memory of past inputs through loops in its architecture in equation (9), Figure 4. This ability allows RNNs to effectively recognize patterns and dependencies within sequential data, making them suitable for demand prediction.

The ANN model architecture

$$Y= f(\Sigma_{i-1}^{n} w_i x_i + b) \quad (8)$$

Where: y is the outpout of the neuron,f is the activation function, w_i are the weights of the connections from the previous layer, x_i are the inputs to the neuron,b is the bias term,n is the number of inputs to the neuron.

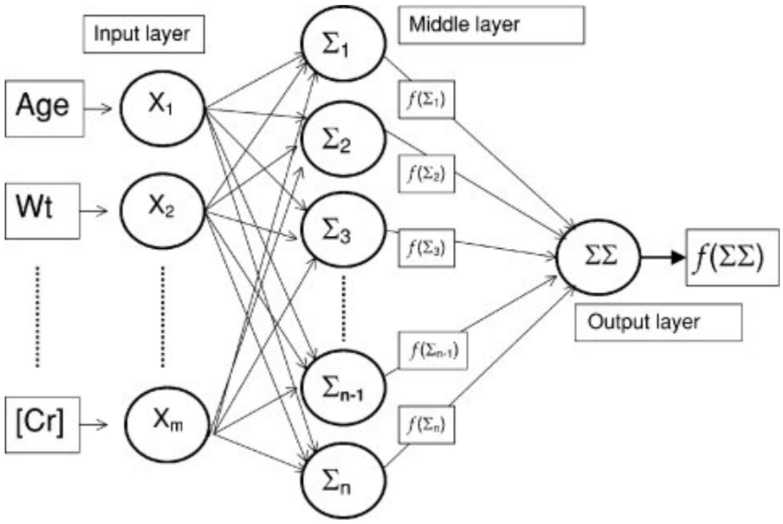


Figure 3 Cell structure of the ANN

The RNN model architecture

$$h_t = f(w_{hh}h_{t-1} + w_{xh}x_t + b_h) \quad y_t = f(w_{yh}h_t + b_y) \quad (9)$$

Where: h_t is the hidden state at time step t,f is the activation function, w_{hh} is the weight matrix for the input connections, h_{t-1} is the hidden state at the previous time step, x_t is the input at time step t, b_h is the bias term for the hidden layer. w_{yh} is the weight matrix for the output layer, h_t *and* b_y are the bias vectors for the hidden state and output layer respectively.

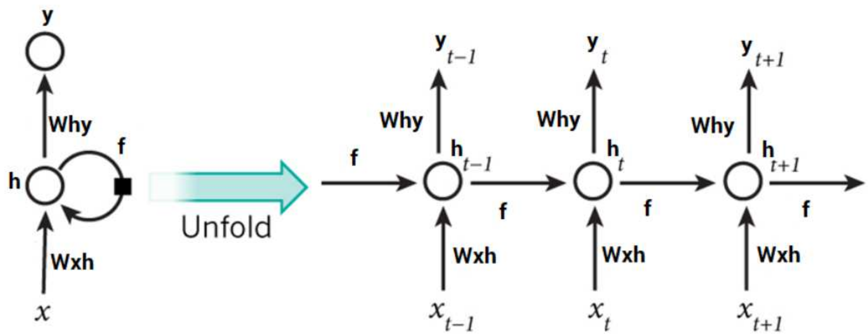


Figure 4 Cell structure of the RNN

3.4 Gradient boosting and final output prediction

After selecting the ANN and RNN models based on their performance metrics, we developed a pioneering hybrid model that integrates predictions from both models as inputs to a gradient boosting algorithm, as depicted in Figure 5. This innovative approach aims to capitalize on the diverse strengths of each model to enhance the overall predictive performance.

GB, a powerful ensemble learning technique, combines multiple weak learners (such as the ANN and RNN models) to create a robust predictive model. During the training phase, the GB model iteratively improves its predictions by minimizing errors from individual weak learners. By focusing on poorly predicted data points from previous iterations, the model gradually refines its predictions.

Once trained on the combined predictions from the ANN and RNN models, the GB model generates final output predictions. These predictions leverage insights from both models to accurately forecast future demand patterns.

By incorporating the strengths of both the ANN and RNN models through GB, the final output predictions are expected to be more robust and accurate, providing valuable insights for decision-making and resource allocation in demand forecasting scenarios.

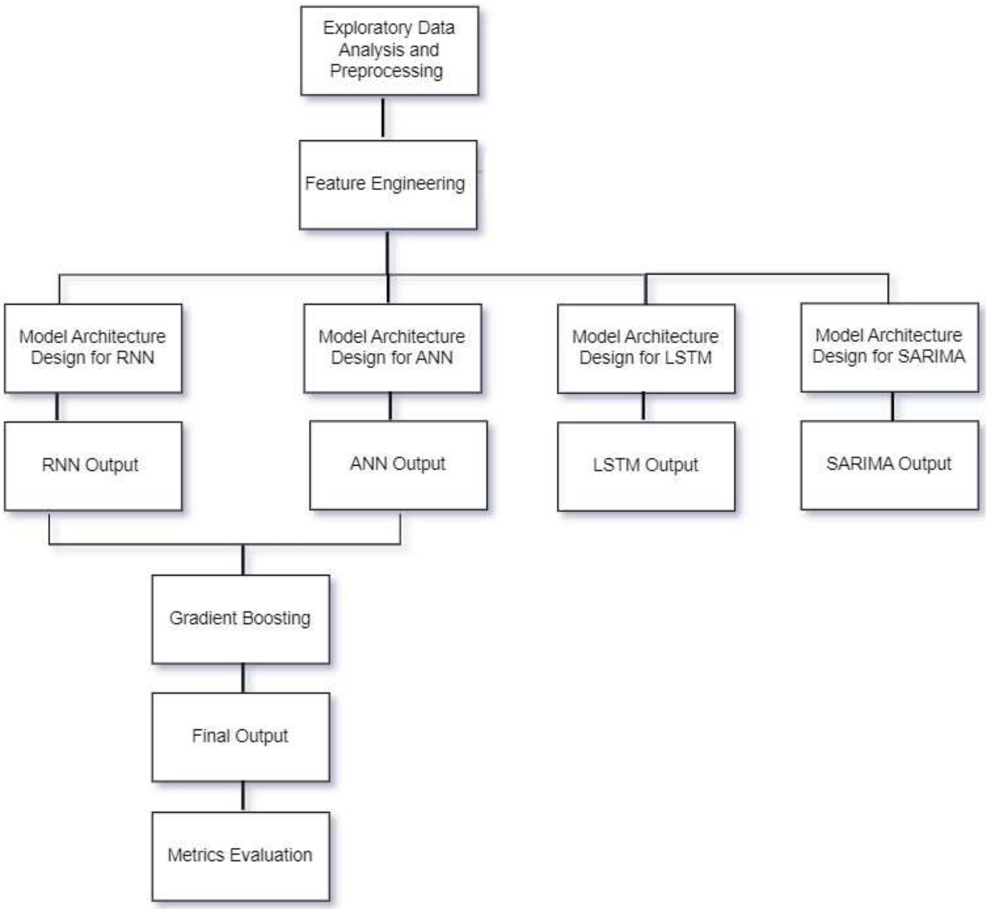
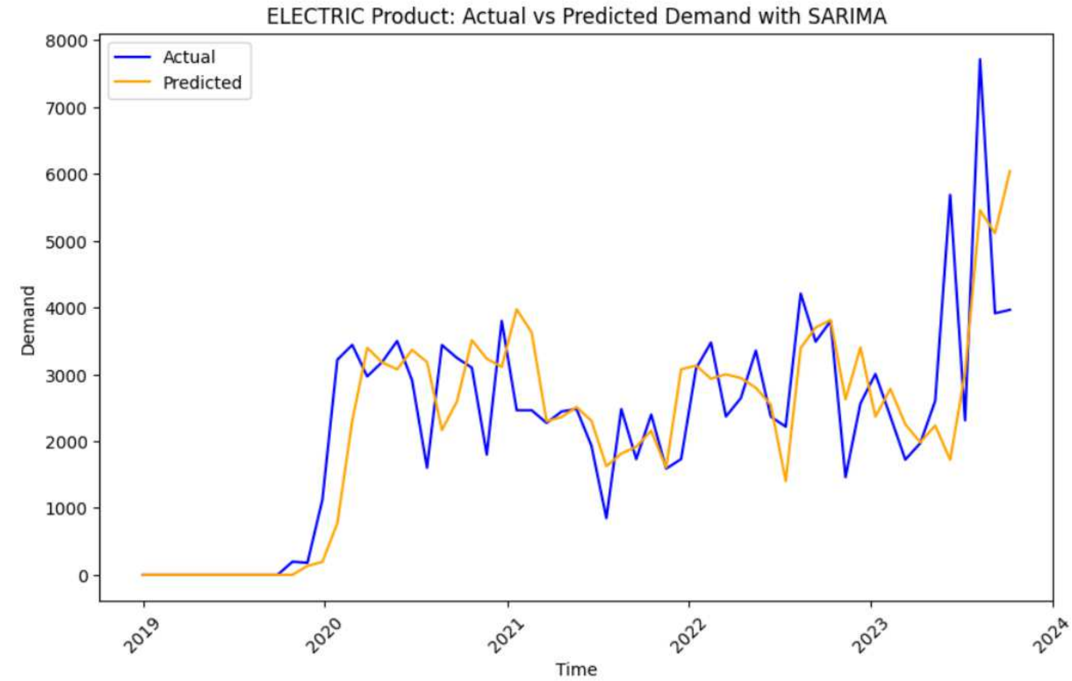


Figure 5 Demand forecasting with single and hybrid models

4 Results analysis and discussion

4.1 Models output

The models were compiled to visualize their performance. Through visual inspection of these plots, we can observe the performance of each model in capturing the underlying patterns and trends in the demand data.These plots in, Figure 6 and Figure 7, provide a graphical representation of the predicted values compared to the actual values, allowing for a qualitative assessment of each model's predictive capabilities.When comparing the LSTM and SARIMA models, we observe distinct patterns in their predictive capabilities.



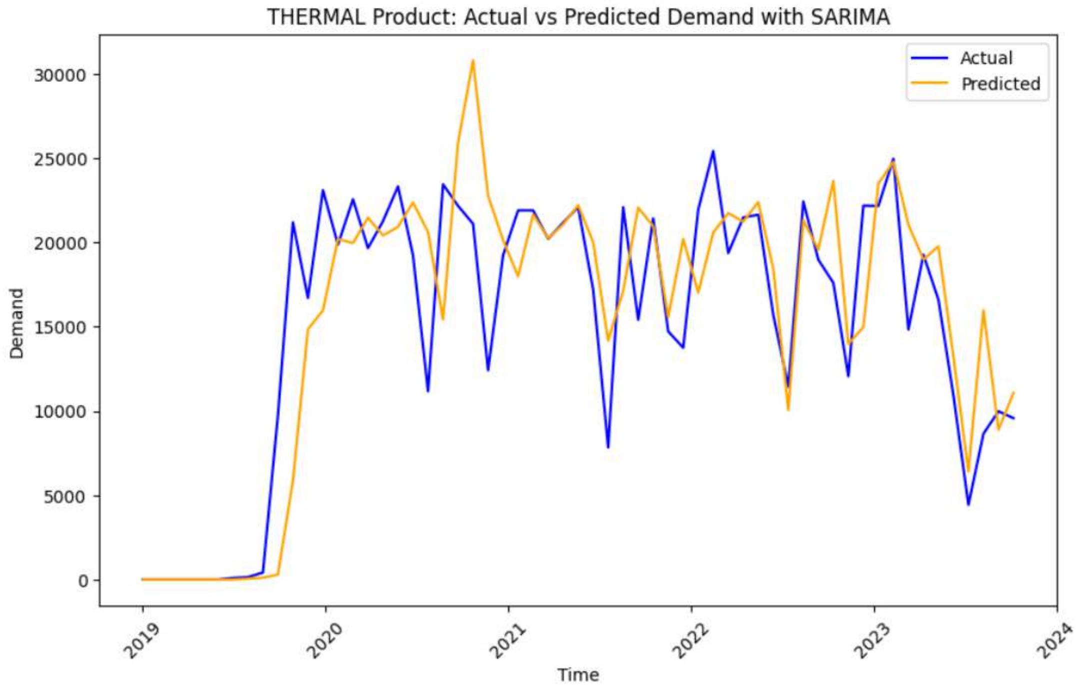


Figure 6 Product demand prediction using the SARIMA model (Actual vs. Predicted)

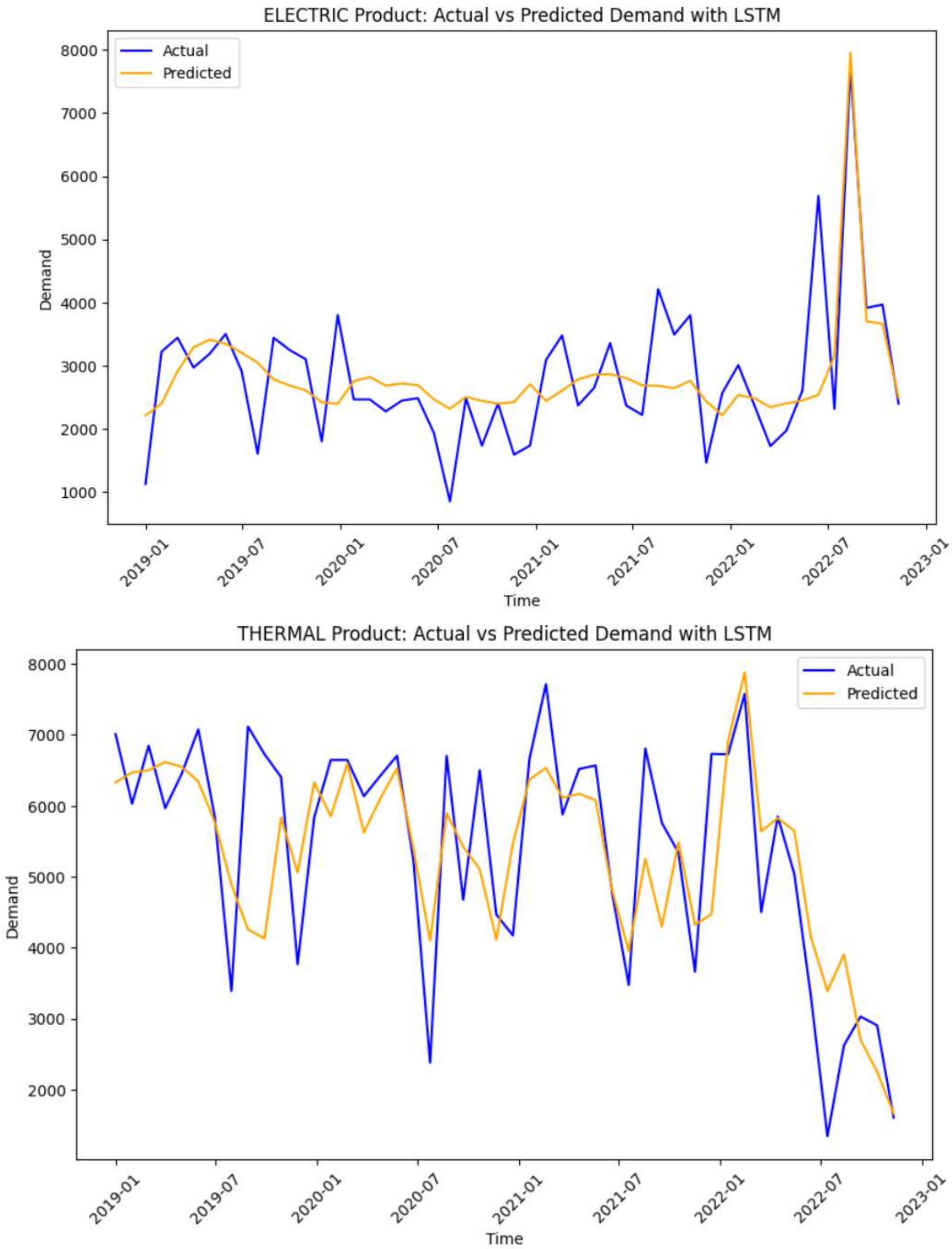


Figure 7 Product demand prediction using the LSTM model (Actual vs. Predicted)

The LSTM model uses the following hyperparameters: a look-back period of 12 time steps, 50 LSTM units with 'relu' activation, an input shape of (12, 1), a dense layer with 1 unit, the 'adam' optimizer, 'mse' as the loss function, 900 epochs for training, a batch size of 32, and a verbosity level of 0.For the SARIMA model the hyperparametres used are: order (p, d, q) for both thermal and electric products: (1, 1, 1) and seasonal order (P, D, Q, s) for both thermal and electric products: (1, 1, 1, 12).

The LSTM plot demonstrates stronger performance compared to SARIMA, aligning more closely with the actual demand values. Despite its complexity, LSTM effectively captures long-term dependencies in sequential data, contributing to its ability to predict customer demand in the automotive sector. However, while LSTM excels in capturing complex temporal relationships, there may still be room for improvement in certain aspects of its predictive accuracy.

In contrast, the SARIMA plot shows relatively weaker predictive performance compared to LSTM. While SARIMA is capable of modeling seasonality and temporal dependencies, it may struggle to fully capture the complexities of the demand data in this context. Its performance may be affected by the challenges posed by the automotive demand dynamics, resulting in less accurate predictions compared to LSTM.

As the performance of both LSTM and SARIMA still falls short of desired accuracy levels, we address this by exploring an ANN model.

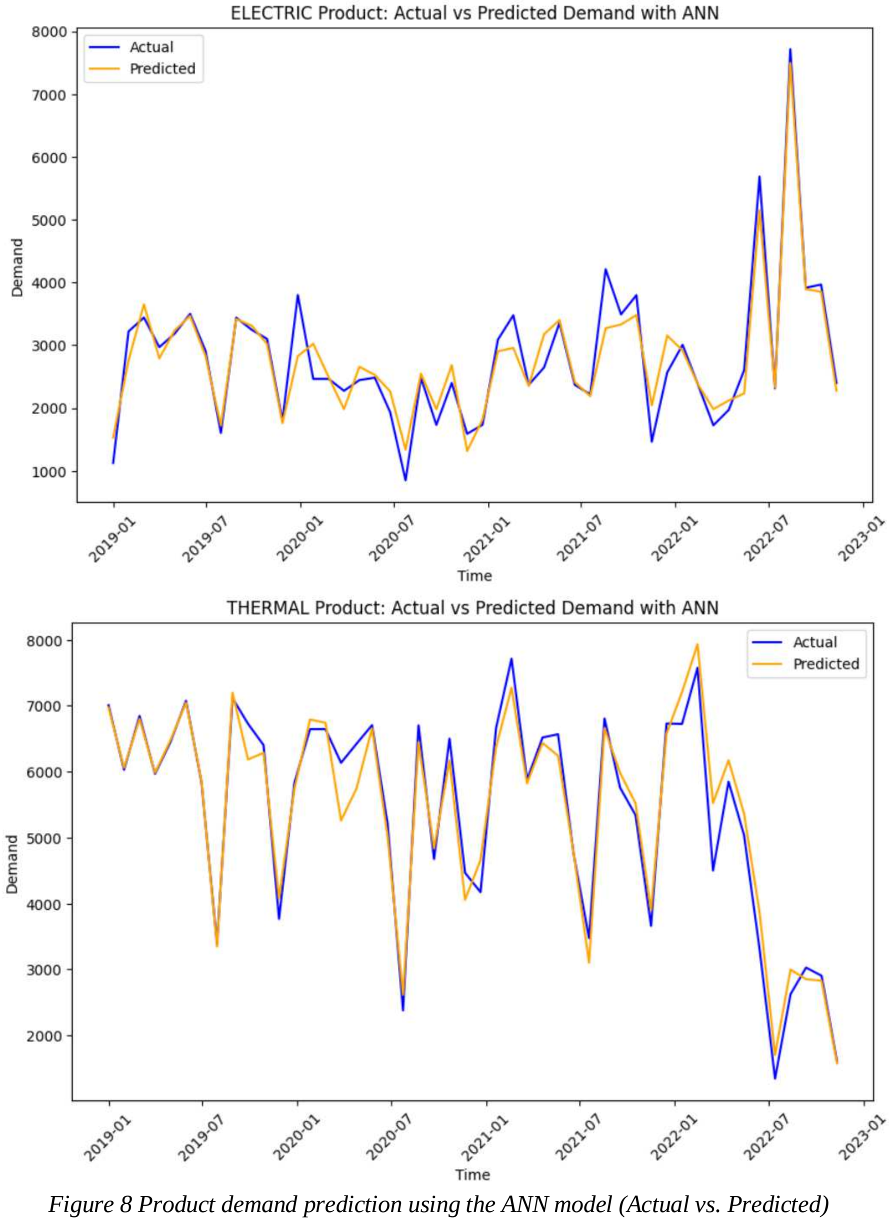


Figure 8 Product demand prediction using the ANN model (Actual vs. Predicted)

The ANN model, in Figure 8, demonstrates superior accuracy compared to both LSTM and SARIMA for both products. Its ability to effectively capture the complex patterns in the demand data suggests that ANN's architecture and learning mechanisms are well-suited for modeling the intricacies of automotive demand dynamics.

The ANN model uses the following hyperparameters: a look-back period of 12 time steps, 50 units in the first dense layer with 'relu' activation, 1 unit in the output layer, the 'adam' optimizer, 'mse' as the loss function, 800 epochs for training, a batch size of 32, and a verbosity level of 0.

In light of the superior performance demonstrated by the ANN model and the inherent ability of RNN architectures to capture sequential dependencies effectively, we employ the RNN model to further enhance predictive accuracy and address the challenges.

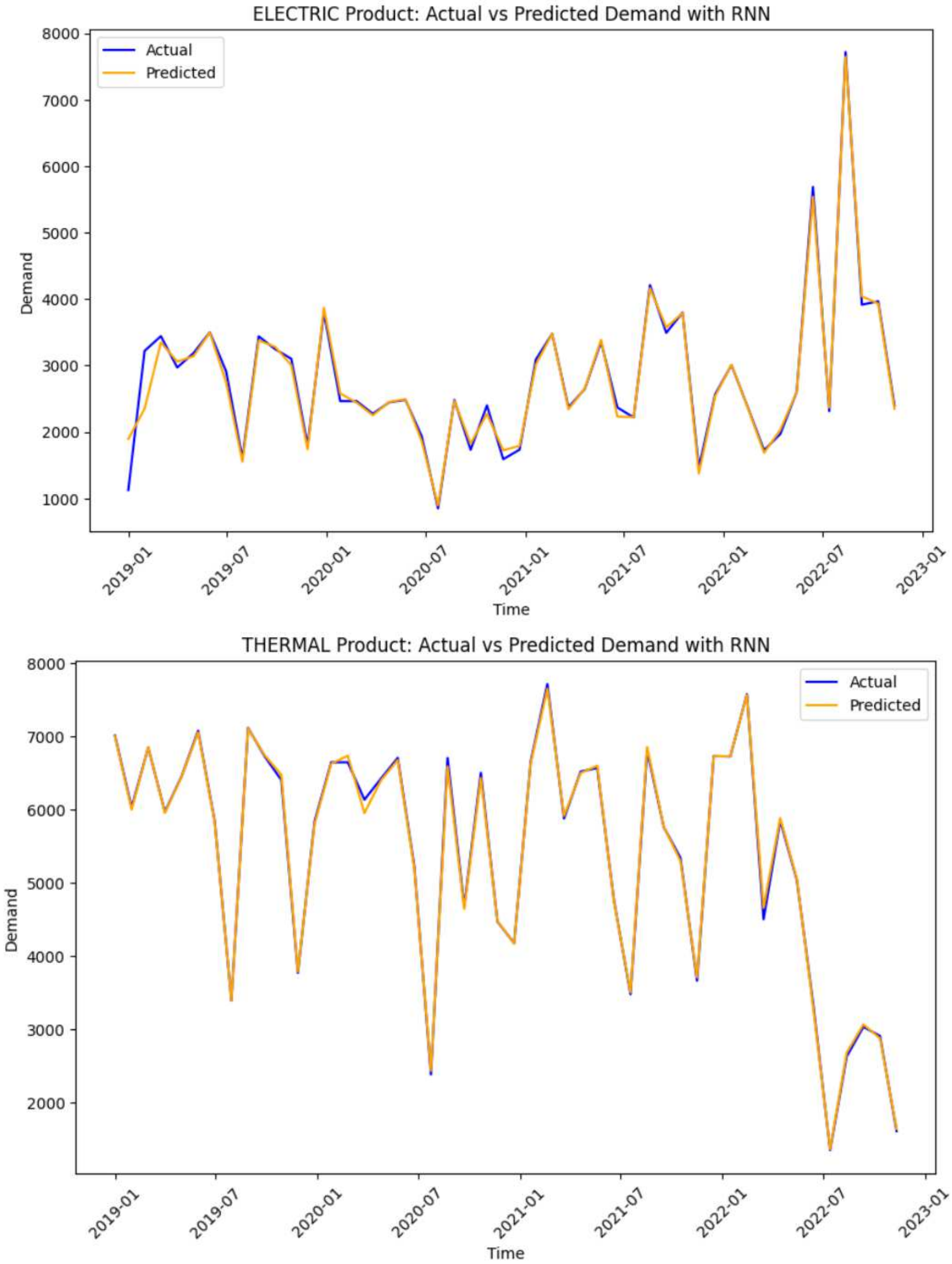


Figure 9 Product demand prediction using the RNN model (Actual vs. Predicted)

The RNN model hyperparameters are as follows: a look-back period of 12 time steps, 50 SimpleRNN units, an input shape of (12, 1), a single unit in the dense layer, 'adam' optimizer, 'mse' loss function, 900 epochs for training, a batch size of 32, and a verbosity level of 0.

The RNN model demonstrates, in Figure 9, the highest level of accuracy, with predicted values closely aligning with actual ones. This suggests that the RNN model effectively captures the underlying patterns and temporal dependencies in the data, making it the most reliable predictor among the single models evaluated.

To further boost the model's performance, we employ a hybrid approach that leverages the strengths of multiple models. Specifically, we combine outputs from both the ANN and RNN models and use them as input for the GB model.

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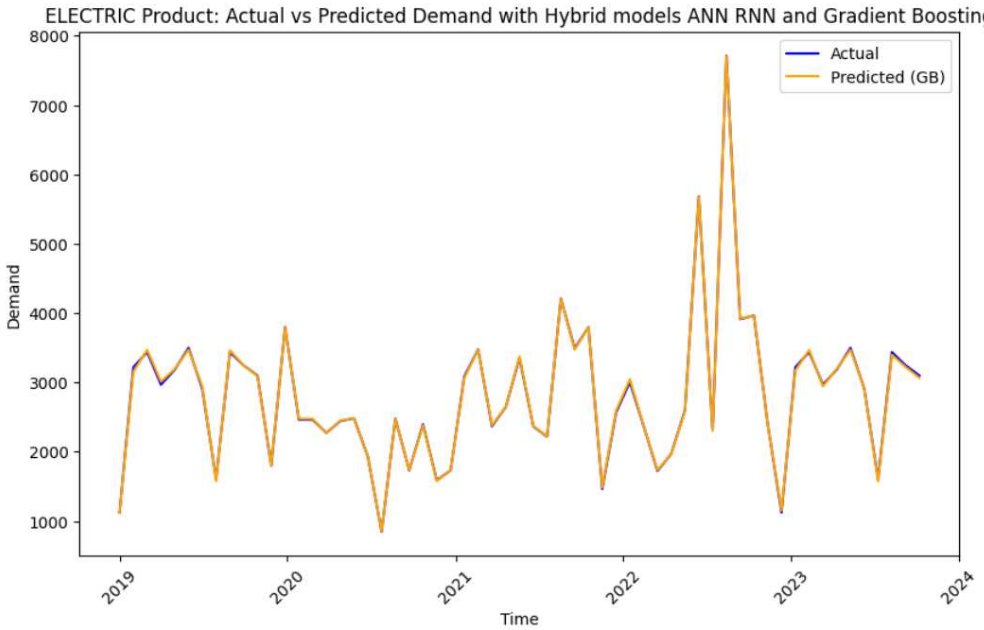

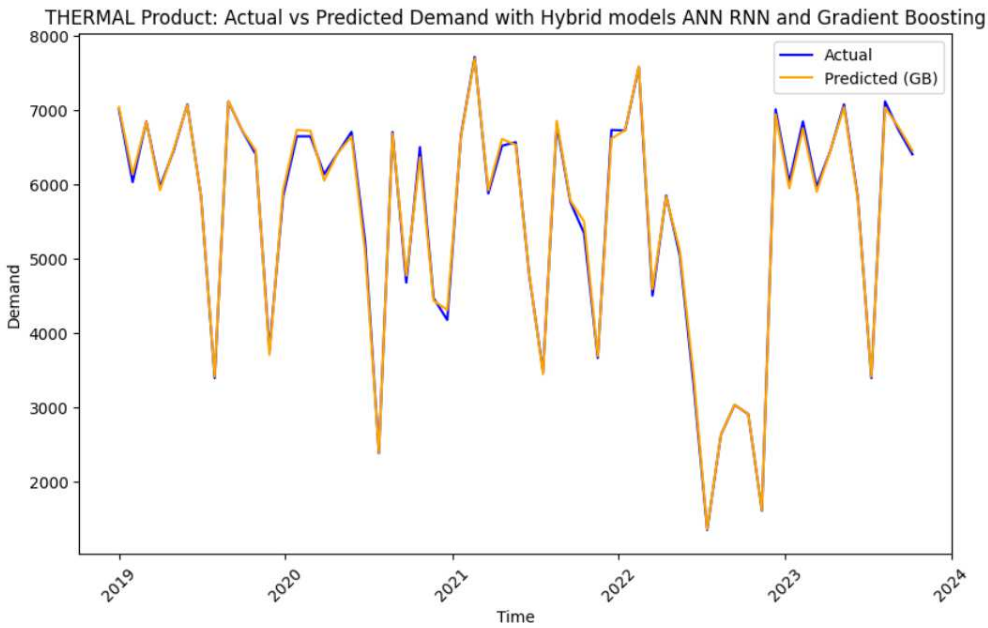

Figure 10 Product demand prediction using the hybrid model ANN-RNN and Gradient Boosting model (Actual vs. Predicted)

The GB model employs default hyperparameters provided by scikit-learn's GradientBoostingRegressor (Figure 10). These include using decision trees as base estimators, 100 estimators, a learning rate of 0.1, a max depth of 3 for each tree, a minimum number of samples required to split an internal node set to 2, a minimum number of samples required to be at a leaf node set to 1, and subsampling of the training dataset set to 1.0.

The GB emerges as the most effective model among the ensemble, outperforming the ANN, RNN, LSTM and SARIMA models. The hybrid architecture combines the complementary capabilities of ANN and RNN, effectively capturing complex patterns and sequential dependencies. Additionally, it leverages the ensemble learning technique of GB to enhance predictive accuracy.

By integrating diverse modeling approaches, we optimized the model's performance, aiming to achieve superior accuracy in forecasting automotive demand dynamics. This makes the hybrid model the optimal choice for customer demand forecasting in our case.

4.2 Metrics evaluation

We conducted a comprehensive evaluation of the performance of our demand forecasting models using two common metrics, MAE (10) and MSE (11).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \widehat{Y}_i| \quad (10)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2 \quad (11)$$

Where: Y_i represents the actual value, $\widehat{Y}_i$ represents the predicted value, and n represents the total number of observations.

These metrics were selected due to their effectiveness in quantifying the accuracy and reliability of predictive models, they capture different aspects of model performance. MAE focuses on the average magnitude of errors, while MSE considers both the magnitude and variance of errors.

By comparing MAE and MSE across SARIMA, LSTM, ANN, RNN, and GB models, we analyzed each model's accuracy and precision. The Table 1, below summarizes the performance metrics for both single and hybrid models.

Table 1 Performance metrics analysis for single and hybrid models for products

Metrics	Products	SARIMA	LSTM	ANN	RNN	GB (Hybrid model)
MAE	Electric	619.84	616.27	239.40	88.80	12.77
	Thermal	3014.96	776.62	248.06	96.70	37.18
MSE	Electric	924692.21	662561.52	111265.48	33114.56	332.34
	Thermal	20399280.60	1067173.73	111110.79	35855.71	2916.64

SARIMA exhibits relatively high MAE and MSE values across both electric and thermal product categories. This suggests that SARIMA's predictions deviate significantly from the actual values, indicating limited accuracy in demand forecasting.

LSTM performs better than SARIMA but still shows relatively high MAE and MSE values. While LSTM effectively captures some long-term dependencies in the data, its predictive accuracy falls short compared to the hybrid model with gradient boosting.

ANN demonstrates improved performance compared to SARIMA and LSTM, with lower MAE and MSE values. However, it still lags behind the hybrid model with GB, indicating room for improvement in accuracy.

RNN exhibits relatively low MAE and MSE values compared to SARIMA, LSTM, and ANN. It demonstrates strong performance in capturing underlying patterns and temporal dependencies, making it a reliable predictor among the individual models.

However, despite the similarity in products characteristics, there are significant differences in the MAE and MSE values between the thermal and electric products across all models. This discrepancy indicates that the predictive accuracy varies depending on the type of product, with the thermal product consistently yielding higher MAE and MSE values compared to the electric product. These findings suggest that the models may perform differently when applied to different types of products.

Overall, the hybrid model combining RNN and ANN with GB consistently achieves the lowest MAE and MSE values across both electric and thermal product categories. This indicates superior accuracy in demand prediction compared to individual models. The ensemble of RNN and ANN, combined with GB, effectively minimizes prediction errors and enhances the overall predictive performance.

5 Conclusions

In conclusion, this research paper has investigated various predictive models for demand forecasting in the automotive sector. Through comprehensive analysis and evaluation, we have demonstrated the effectiveness of a hybrid model combining RNN and ANN with GB in predicting demand, surpassing single models such as SARIMA, LSTM, ANN, and RNN.

The results indicate that while single models exhibit varying degrees of accuracy in demand prediction, the hybrid model consistently outperforms them. By leveraging the strengths of multiple models and ensemble learning techniques, the hybrid model demonstrates superior predictive accuracy, as evidenced by lower MAE and MSE values across both electric and thermal product categories.

In the context of demand forecasting, we looked into the performance difference between LSTM and ANN models. Remarkably, our test findings showed that, in terms of prediction accuracy, the ANN model performed better than the LSTM model, contradicting the widely accepted belief that LSTM performs better when it comes to time-series data processing. Despite the surprising performance difference that was found, this study emphasizes how crucial it is to comprehend how various models behave in practical settings. We can learn many things about the advantages, disadvantages, and task-specific applicability of LSTM and ANN models by methodically investigating the elements causing the performance disparity between them. Future studies and real-world applications in demand forecasting and other time-series prediction challenges will be greatly impacted by this insight. It highlights the requirement for careful model selection, thorough experimentation, and continuous refinement to ensure optimal performance and reliability in real-world settings.

It's crucial to recognize this study's limitations, though. The use of historical data, which might not accurately reflect unexpected or unexpected shifts in demand patterns, is one drawback. Furthermore, the specifics of the automobile industry and the accessibility of data may have an impact on how effective the hybrid model is.

Future studies should investigate how external factors like customer preferences, changes in legislation, and economic situations affect the accuracy of demand forecasting. Furthermore, examining the hybrid model's scalability and computing efficiency in scenarios of real-time demand forecasting would yield important information for useful application in the automobile sector.

Moreover, the integration of advanced methodologies like anomaly detection algorithms and reinforcement learning may improve the resilience of demand forecasting models, especially in situations that are uncertain and dynamic. Furthermore, investigating the incorporation of data from non-traditional sources like social media, IoT devices, and SC networks may present new perspectives into demand forecasting and enhance its precision.

In summary, this study offers valuable insights into demand forecasting within the automotive sector. However, it identifies specific limitations and areas for improvement, underscoring the need for further research to advance the field towards more accurate and actionable forecasting methodologies.

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