

Presenting a Demand Model for Product Development Customization with a Marketing 5.0 Approach in the Business Sector Using Deep Learning Algorithms

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Article Info	ABSTRACT
Article type: Research Article Article history: Received 16 February 2026 Received in revised form 5 April 2026 Accepted 14 September 2026 Published online 1 October 2026 Keywords: demand model, product development customization, Marketing 5.0 approach, deep learning, lighting industry	Demand forecasting in the energy sector is of high importance, to the extent that many studies have focused to this field, attempting to estimate energy demand using novel methods. Moreover, Marketing 5.0 is characterized by artificial intelligence-based features and has thus moved away from traditional marketing methods. The combination of these two concepts, demand forecasting and Marketing 5.0, necessitates the use of artificial intelligence algorithms. In the current study, a demand model for product development customization with a Marketing 5.0 approach is presented. In this regard, deep learning algorithms, such as Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNN), and Deep Neural Networks (DNN), were used. Four features—firm size, firm revenue, economic growth, and firm electricity consumption cost—were considered as factors influencing demand. The results of implementing the deep learning algorithms showed that the Long Short-Term Memory neural network (95%), the Recurrent Neural Network (94%), and the Deep Neural Network (93%) had the highest accuracy in demand forecasting. Furthermore, the firm's electricity cost had the most significant impact on the presented model, followed by firm revenue. The third rank belongs to firm size, and economic growth holds the final rank in terms of electricity demand in the industrial and business sectors.

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1) Introduction

In the modern era, energy demand forecasting has become a fundamental and crucial component of efficient energy management. Energy consumption is increasing for various reasons, including population growth, rising building energy needs, and the expansion of technological applications (Bauzon et al., 2025). According to available data, global energy consumption is projected to increase by 70% by 2040. This alarming figure necessitates the development of advanced predictive models for energy demand, which are vital and essential for optimizing energy consumption (Parizad et al., 2025). On the other hand, Marketing 5.0 refers to the use of human-mimicking technologies to create, communicate, deliver, and enhance value throughout the customer journey (Akter et al., 2024; Keshavarz & Liu, 2026). One of the important themes of Marketing 5.0 is what is called future technology, meaning a group of technologies aimed at simulating the abilities and capabilities of human marketers. These technologies include artificial intelligence, natural language processing, sensors, robotics, augmented reality, virtual reality, the Internet of Things, and blockchain. These technologies, combined, enable the realization of Marketing 5.0 (Ghimire et al., 2025).

Therefore, it can be said that one of the principles of Marketing 5.0 is the use of artificial intelligence (AI). AI algorithms are capable of predicting and classifying any phenomenon, including demand (Farhang & Safi-Esfahani, 2020). In the lighting and energy industry, demand forecasting is of great importance, and AI algorithms, specifically deep learning algorithms inspired by the human neural network, can be beneficial in this regard (Sakib et al., 2025). One of the most energy-intensive and, in fact, highest-demand sectors is the business and production sector. Therefore, it is necessary to estimate the energy demand of the production sector. According to statistics from 2024, the industrial sector's consumption accounted for 35% of total consumption, while this figure for the household sector was 32%, indicating that the industrial sector surpasses the household sector. Furthermore, it should be noted that the growth in electricity consumption in the industrial sector, compared to the previous year, was 5.8%. Consequently, it can be said that the industrial sector is an energy-sensitive sector, and by understanding the influencing factors, more accurate planning can be done regarding product development management in this sector (He et al., 2025).

This research aims to present a demand model for product development customization with a Marketing 5.0 approach in the business sector. Therefore, the focus of the current research is solely on the business sector rather than the household sector. To predict demand, deep learning algorithms are used, which have a higher capability compared to machine learning algorithms. The structure of the present article is as follows: A literature review and research gap are extracted, followed by the research methodology, the analysis of findings, and finally, the conclusion.

2) Literature Review

This section reviews the most important research in the field of demand forecasting using artificial intelligence algorithms and based on fifth-generation marketing and product development. The conducted research pertains to the last 5 years. Based on the literature review, research gaps are identified at the end. Kumar et al. (2021) addressed stock market prediction using computational intelligence and performed this based on demand forecasting. Zhang et al. (2021) focused on tourism demand forecasting using a decomposed deep learning approach. Jha and Pande (2021) presented a

time series forecasting model for supermarket sales. Goyal et al. (2021) analyzed the demand and market capacity of air taxi and airport shuttle markets. Feizabadi (2022) performed demand forecasting using machine learning based on supply chain performance. Falatouri et al. (2022) conducted predictive analysis for demand forecasting, comparing SARIMA and Long Short-Term Memory Network algorithms in the retail supply chain.

The effects of artificial intelligence and machine learning on customer behavior (Krishnamoorthy & Sanaei, 2026), demand forecasting, and chatbots in the realm of digital marketing were investigated by Akter et al. (2024) and ArfaeiYazdiPour et al. (2026). Emotion-based predictive models for online purchases in the field of fifth-generation marketing using a literature review were examined by Gooljar et al. (2024) and Safizadeh et al. (2026).

Bauzon et al. (2025) performed electricity load forecasting based on deep learning algorithms for optimal energy demand prediction in the Philippines. Sakib et al. (2025) developed an associative deep learning framework for energy demand forecasting using genetic algorithm-based feature selection. He et al. (2025) used machine learning techniques to optimize load demand forecasting in air conditioning systems for the GRU/IASO model. Parizad et al. (2025) investigated added robustness in household demand forecasting. They combined statistical loss functions with validation enhancement in machine learning hyperparameter optimization. Ghimire et al. (2025) presented a model for electricity demand forecasting in explainable deep fuzzy networks. The researchers incorporated situational predictors to enhance accuracy and provided deep insights through point predictions and probabilistic confidence intervals.

Based on the conducted literature review, it can be observed that the research primarily focuses on presenting demand forecasting models without considering fifth-generation marketing and new product development. Although numerous studies are conducted in the field of energy consumption and its demand forecasting, the specific topic of fifth-generation marketing has not been addressed, and this can be considered a research gap. The current research attempts to bridge this gap.

3) Research Method

The present research is applied in terms of its objective and developmental nature. This research uses deep learning algorithms to predict demand for product customization and development with a Marketing 5.0 approach in the business sector. In fact, this research aims to predict demand for industries and businesses, and does not focus on residential demand. The variables of the present research are introduced in the table below.

Table 1. Research Variables

Row	Variable Title	Variable Symbol	Variable scale
1	Economic growth	GDP	Quantitative
2	Firm size	FS	Quantitative
3	Firm revenue	FI	Quantitative
4	Firm electricity costs	EC	Quantitative
5	Demand rate	Demand	Quantitative

Therefore, based on the above table, four input variables are identified as determinants of demand. The above model can be drawn in the following conceptual model.

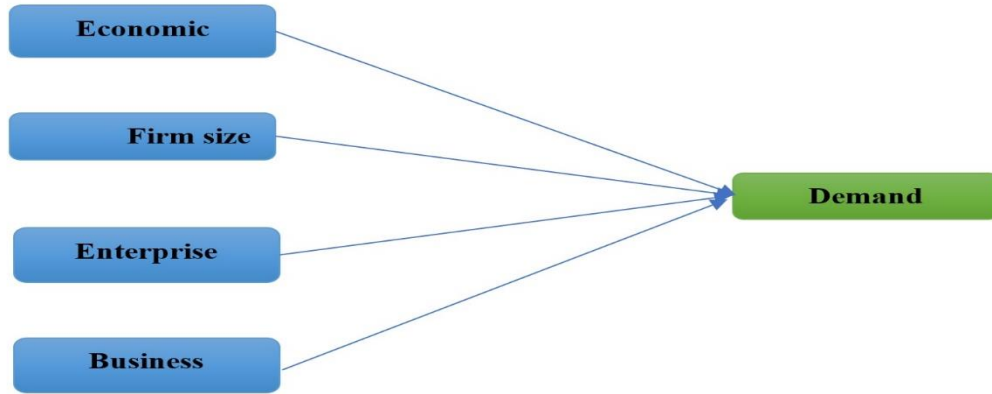


Figure 1. Conceptual Model of the Research

Based on Figure 1, it is observed that there are four input variables. In the residential electricity demand model, there were five input variables, where firm size was considered as household size, firm income as household income, and firm electricity cost as residential unit electricity cost. Additionally, in the current research, economic growth is considered instead of GDP, and the population variable has been removed. Therefore, the presented model is considered the determinant of electricity demand based on Marketing 5.0. Data collection is based on datasets from various companies. Firm size is determined by the number of employees. Firm income is extracted from the profit data of firms listed on the Tehran Stock Exchange, and electricity cost is derived from the data of the studied companies. Economic growth data is collected from the Statistical Center of Iran. Based on the total collected data, a dataset is formed, which can serve as the basis for implementing the current research model. The data is panel data, a combination of company information and time series from 2001 to the present. Since deep learning algorithms are used in this research, a large volume of data is required, which is collected in this study. The algorithms used include deep learning algorithms as follows:

- Long Short-Term Memory Neural Network Algorithm
- Recurrent Neural Network Algorithm
- Deep Neural Network Algorithm

The algorithms were predictive, and thus, they estimate demand, with results calculated in terms of error and accuracy.

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

In the above relation, the averaging operation is performed by the following relation:

$$\frac{1}{n} \sum_{i=1}^n Y_i \quad (2)$$

The second part, which is:

$$\sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (3)$$

It calculates the squared error of each data point, and thus, MSE is the mean of the squared errors. Based on this, the total error of the system can be estimated, and the lower this error, the better the results obtained from the algorithms. The general steps for the current research are as follows:

The Long Short-Term Memory (LSTM) algorithm is a type of recurrent neural network where the input can be continuous, making it a suitable algorithm for time-series data (Taghizadeh et al., 2026). In the current research, the data is numerical, whereas the Short-Term Memory algorithm can work with various data types such as audio and images, and is capable of handwriting recognition, machine translation, speech recognition, and even controlling robots and video games. A Long Short-Term Memory algorithm includes the following four components.

- c_t : Cell content
- i_t : Cell content
- o_t : Output gate
- f_i : Oblivion gate

Input gates, output gates, and forget gates are vectors with values between zero and one, which determine whether old information is retained and new information is added. In these gates, a value of one means that information passes through, while a value of zero indicates that information is deleted. A recurrent neural network, also known as a recursive neural network, is a type of neural network in which connections between nodes of a directed graph are along a time sequence, causing the algorithm to exhibit dynamic behavior. The Hopfield type of this network is such that all connections between layers have the same size and require constant inputs. The deep neural network is the third algorithm used in the present research. It consists of a set of neurons organized in layers, including input, hidden, and output layers. Each neuron in one layer is connected to neurons in the previous and subsequent layers, and these connections are adjusted by weights. The input layer receives raw data, the hidden layer processes the raw data and extracts more complex features, and the output layer produces the final output. This output can be a classification, such as object recognition, or a numerical value, such as a prediction or estimate.

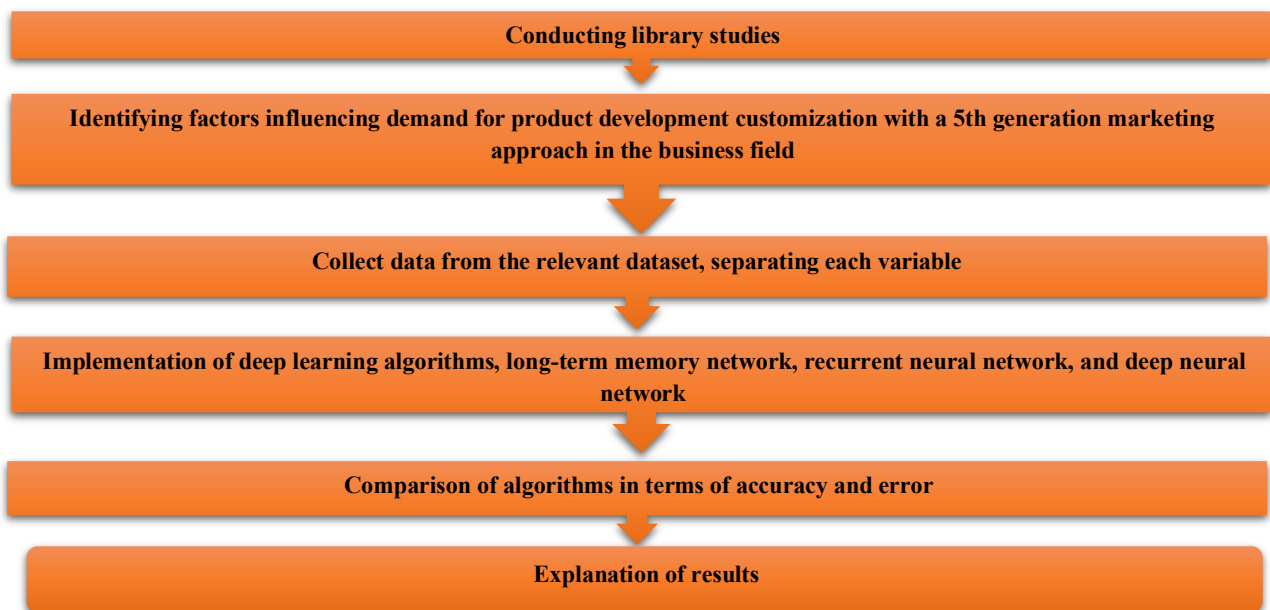


Figure 2. Research Steps

4. Data Analysis

As mentioned in the Methodology Section, three algorithms—Long Short-Term Memory Neural Network, Recurrent Neural Network, and Deep Neural Network—are used as the target algorithms for implementing the proposed model. Accuracy and MSE are the evaluation metrics for the algorithms used. The results of implementing these algorithms, broken down by accuracy and error, are presented below. The presentation is separated into training data and validation data.

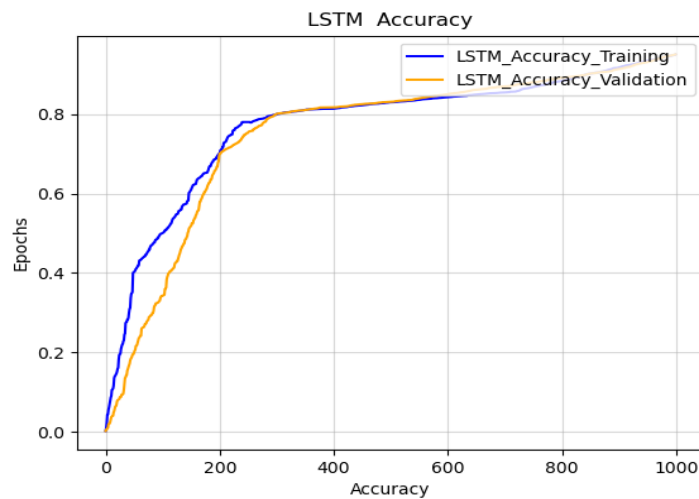


Figure 3. LSTM Algorithm Accuracy

Based on the above figure, it can be observed that the accuracy of the algorithm increases with the number of iterations and approaches the optimal value, while the validation and training curves show significant convergence.

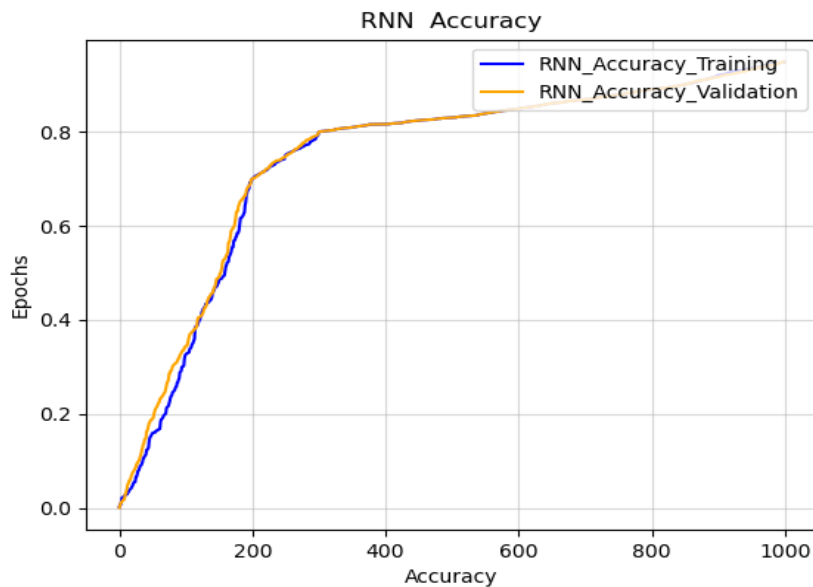


Figure 4. RNN Algorithm Accuracy

Figure 4 shows the results of increased accuracy for the RNN algorithm. In this algorithm, too, the accuracy of the algorithm has increased with an increase in iterations, indicating the evolutionary nature of the deep learning algorithm.

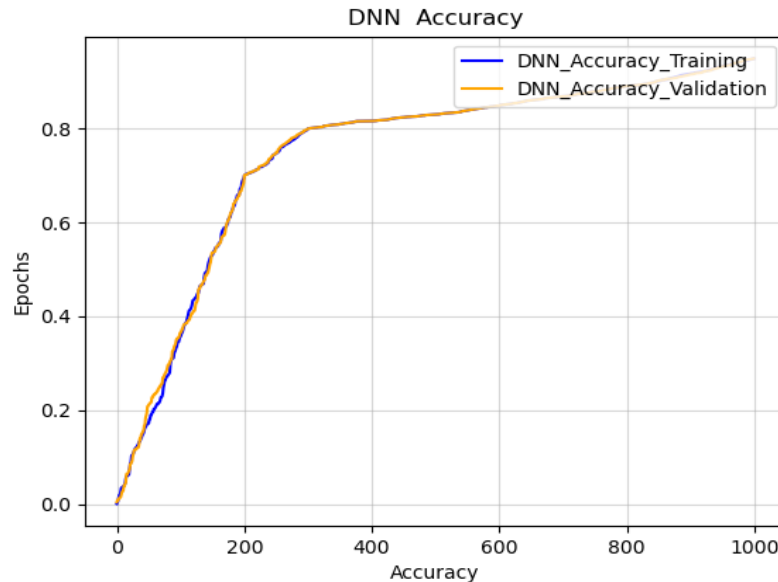


Figure 5. DNN Algorithm Accuracy

In Figure 5, the performance of the DNN algorithm is examined, which has a strong similarity to the RNN algorithm. Therefore, considering the overlap of the validation and training charts and their convergence, the performance of both algorithms can be considered satisfactory.

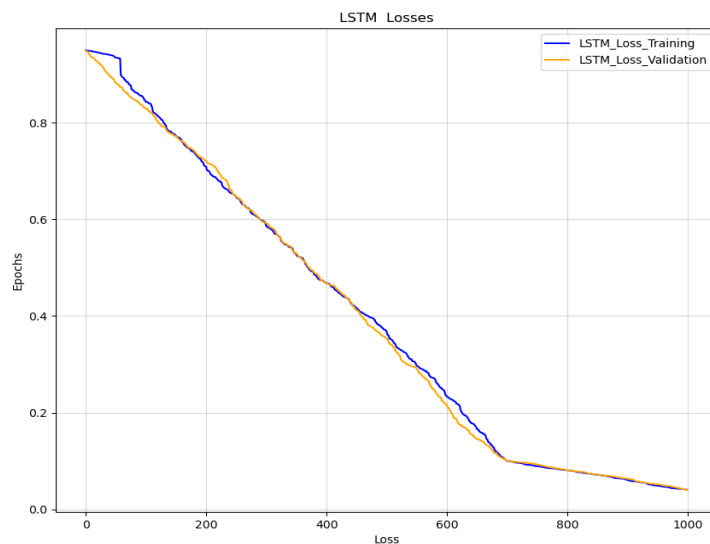


Figure 6. LSTM Algorithm Error

In Figure 6, the downward trend of the LSTM algorithm error graph is clearly visible, indicating that the error rate decreases with an increase in iterations, resulting in a reduction of error for the aforementioned algorithm.

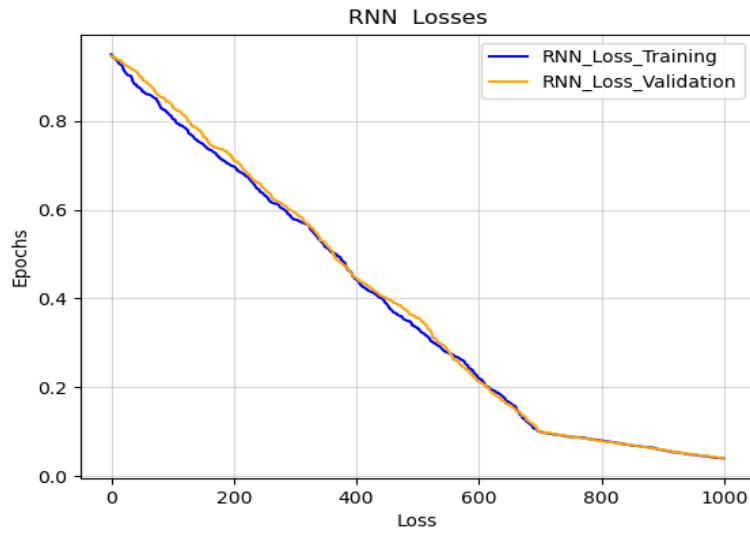


Figure 7. RNN Algorithm Error

Figure 7 shows the reduction in the RNN algorithm's error based on the number of iterations. It can be said that the algorithm's performance in error reduction has been positive.

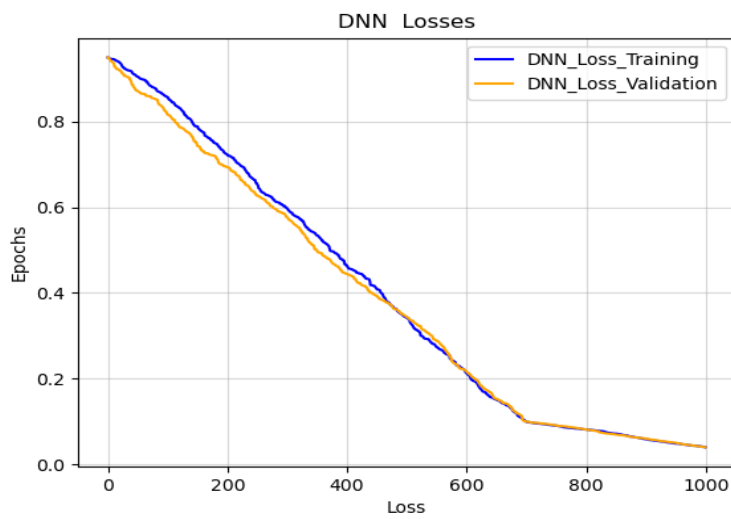


Figure 8. DNN Algorithm Error

Figure 8 shows the reduction in DNN algorithm error with increasing iterations, indicating the optimization of results due to the evolutionary nature of the algorithm.

Next, a comparison of R and MSE values for each algorithm will be discussed. The results are presented in the table below.

Table 2. Comparison of Algorithms in Terms of R and MSE

Algorithm	R	MSE
Long-term memory neural network	0.954	0.012
Recurrent neural network	0.946	0.0248
Deep neural network	0.932	0.0323

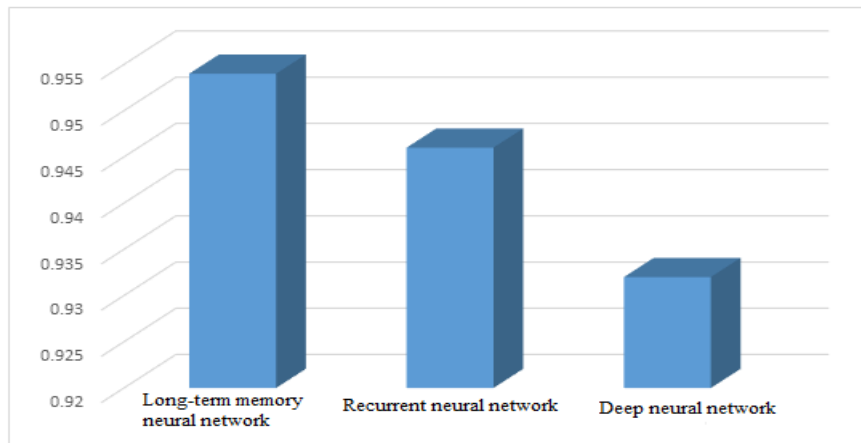


Figure 9. Comparison of Algorithms in Terms of R

Based on Figure 9, it can be observed that the Long Short-Term Memory neural network algorithm has the highest accuracy value, followed by the Recurrent Neural Network and the Deep Neural Network, which ranks third in terms of demand prediction accuracy.

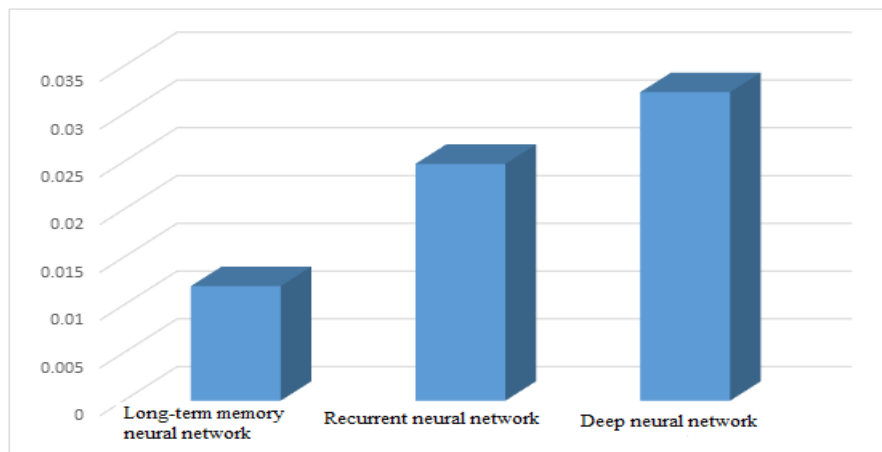


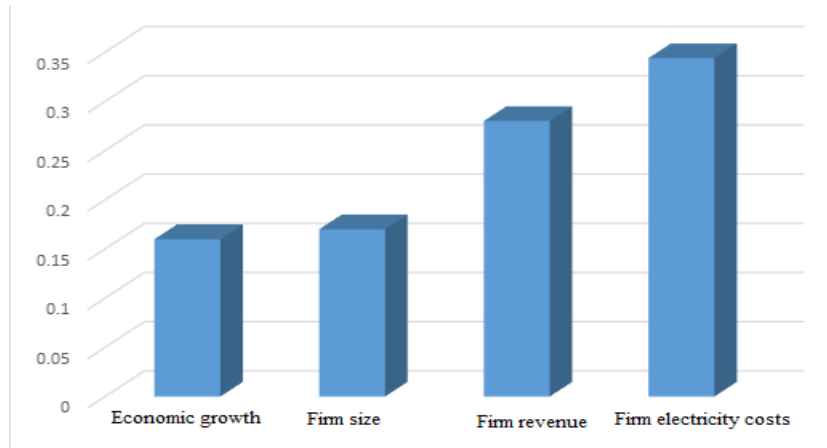
Figure 10. Comparison of Algorithms in Terms of MSE

Figure 10 shows that the lowest error rate belongs to the Long Short-Term Memory neural network, followed by the Recurrent Neural Network and the Deep Neural Network in terms of MSE, indicating the superiority of the Long Short-Term Memory neural network. In fact, just as the Long Short-Term Memory neural network has the highest accuracy in terms of R, it also has the lowest MSE, indicating the strong performance of this algorithm in demand forecasting.

Next, the four input variables are compared and ranked as features or input characteristics to the deep learning model. The results are presented in the Table 3. Based on Figure 11, it can be said that the electricity cost of the enterprise has the most significant impact on the presented model, followed by the enterprise income. The third rank belongs to the enterprise size, and economic growth holds the final rank in terms of electricity demand in the industrial and business sectors.

Table 3. Comparison of Features in Terms of Effectiveness

Row	Variable Title	Percentage of Effect
1	Economic growth	0.16
2	Firm size	0.17
3	Firm revenue	0.28
4	Firm electricity costs	0.344

**Figure 11.** Comparison of Characteristics in Terms of Effectiveness

5. Conclusion and Recommendations

This article presents a demand model for product development customization based on the Generation 5 Marketing approach. The model comprises four input features: electricity cost, enterprise income, enterprise size, and economic growth. The results showed that all four variables can predict more than 95% of the demand in the business and industrial sectors of the economy. This is because the result was obtained from the implementation of the Long Short-Term Memory (LSTM) network algorithm, which was the superior algorithm in the current research. This indicates that 95% of the demand in this sector can be explained by the four aforementioned variables. Among the input variables, electricity cost has the greatest influence on the proposed model, indicating that it is the most significant factor affecting demand. Enterprise income ranks second in importance, which is consistent with previous studies demonstrating that income is a key determinant of demand. Consequently, income has consistently been recognized as an essential variable in demand forecasting models. Enterprise size, which is analogous to household size in residential electricity demand models, ranks third in terms of importance. Finally, economic growth has the lowest importance among the variables considered in the model.

The model presented in the current research regarding electricity and lighting demand proved to be a perfectly consistent and strong model, which can provide relevant authorities with a suitable perspective on understanding influential factors and the extent of each factor's influence. On the other hand, previous research presented a residential electricity demand model, and the model presented in the current research can complement the previous model—i.e., the residential model—because the current model is solely focused on the business and industrial sectors. The deep learning algorithms

evaluated in this study demonstrated strong predictive capabilities, as reflected by their high forecasting accuracy. Among these algorithms, the Long Short-Term Memory (LSTM) model achieved the highest accuracy and the lowest prediction error, making it the most effective approach for the proposed demand forecasting model. These findings suggest that the LSTM algorithm consistently outperforms the other deep learning algorithms considered in this study and can therefore be recommended for similar demand forecasting applications. Future research could integrate the proposed business demand model with residential demand models to develop a comprehensive demand forecasting framework for the lighting industry. In addition, Generation 5 marketing elements can be incorporated into the integrated model to further enhance its predictive performance and practical applicability.

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