Educational Administration: Theory and Practice
2023, 29(2), 602-612
ISSN: 2148-2403
https://kuey.net/
Research Article

Optimizing Digital Supply Chain Management Based On ERP Systems Using Artificial Intelligence With Deep Learning Model

Sohit Reddy Kalluru[1*], Prasanna Kumar Reddy Gurijala[2], Lohith Reddy kalluru[3], Pavana Kumari Gavva[4]

[1*]SAP Solution Architect, Mygo Consulting Inc, Naperville, Illinois, USA – 60563.
[2]SAP Solution Architect, Mygo Consulting Inc, Naperville, Illinois, USA - 60563.
[3]Cloud Developer-2, Hewlett Packard Enterprise, 1701 East Mossy Oaks Road Spring, TX 77389-1767.
[4]Senior Analyst, Nextgen IT Solutions, Plainfield,Illinois,USA – 60544.

Citation: Sohit Reddy Kalluru et, al (2023) Optimizing Digital Supply Chain Management Based On ERP Systems Using Artificial Intelligence With Deep Learning Model, *Educational Administration: Theory And Practice*, 29(2), 602-612
Doi: 10.53555/kuey.v29i2.7609

ARTICLEINFO

ABSTRACT

With the growth and progress of information technology, competition turned out to be more exhaustive on a global scale. Numerous enterprises have predicted that the future of process and supply chain management (SCM) might modify vividly, from scheduling, planning, optimisation, to transportation, with an occurrence of artificial intelligence (AI). Nowadays, people are more involved in machine learning (ML), AI, and other intellectual technologies, with regard to SCM. AI-driven SCM optimization and Enterprise Resource Planning (ERP) systems integration. As industries attempt for active excellence, the convergence of artificial intelligence (AI) and SCM arises as a transformative force in dynamic agility, efficacy, and competitiveness. Over a complete analysis, this abstract inspects the synergistic relationship among AI-driven SCM optimization and the combination of ERP systems, clarifying their collective impact on manufacturing efficiency. Therefore, the study present a new Optimizing Digital Supply Chain Management Based on ERP Systems using Artificial Intelligence (ODSCM-ERPAI) method. The proposed ODSCM-ERPAI technique depends upon the optimization algorithm and DL based prediction process for digital SCM. To achieve this, the ODSCM-ERPAI system originally completes data preprocessing to measure the input signals into a uniform format. Next, the bidirectional long short term memory (Bi-LSTM) model is used for prediction process with the inclusion of improved grey wolf optimization (IGWO) algorithm as a hyperparameter optimizer. To exhibit the improved performance of the ODSCM-ERPAI approach, a wide range of experiments are performed and the outcomes are examined under several aspects. The experimental outcomes reported the enhanced performances of the ODSCM-ERPAI model over the other techniques.

Keywords: Supply Chain Management; Artificial Intelligence; Deep Learning; Enterprise Resource Planning; Long Short Term Memory

1. Introduction

Enterprise resource planning (ERP) processes are generally advanced as individual stand-alone monolithic applications. The majority of methods in this group have a related multi-tier or client-server architecture constructed near a main database server [1]. Normally, in conventional multi-tier stand-alone ERP implementation, crucial application mechanisms are vital for some functionality [2]. ERP method is a general term for an incorporated enterprise computing method. It is an adapted packaged software-based technique, which processes most of an enterprise's data methods necessities. It is a software structure that enables the information flow amongst all functions inside an enterprise [3]. ERP techniques are exclusive to support an organization’s commercial ways. Supply Chain Management (SCM) is a powerful technique to sustain competition benefits and secure performance. To gain a superior competitive ability, SCM is a tactic that intends to reduce costs, offer improved production combinations and distributed methods, and improve customer fulfillment [4]. SCM is a way to control the information flow, services, and products between and inside the firms and also improves sturdy connections between customers and suppliers [5]. Fig. 1 represents the function of SCM.

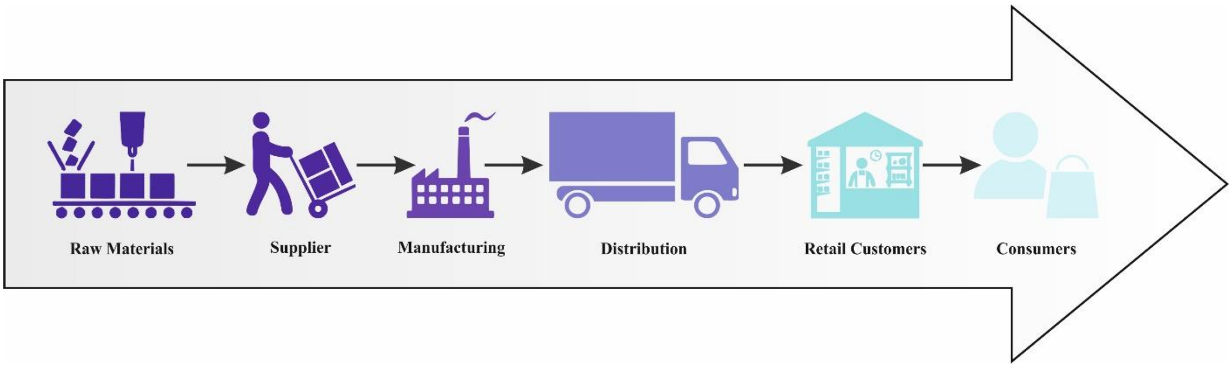

Fig. 1. Function of SCM

The commercial transformation lasts to change quickly, which has completed SCM crucial in sustaining smooth developments in manufacturing enterprises [6]]. The designed supply chain contains several parties, from dealers to end users. SCM is important in guaranteeing business progressions run effectively and efficiently in encountering market demands continually evolving and changing quickly [7]. Changes that occur need applying information technology, which can offer information in real-time to help companies make choices along the flow of the supply chain by applying ERP [8]. The ERP benefits are a combined management technique between business functions, sharing data and information, and accessing and generating information in real-time in a supply chain organization. An ERP method can forecast external and internal environmental behavior such that organizations can control and plan environmental aspects to aid in decision-making with information achieved rapidly [9]. Supply chain incorporation through ERP can also improve collaboration and visibility between suppliers and their companies, allowing better efficacy and speed in the obtaining process [10].
This article presents a new Optimizing Digital Supply Chain Management Based on ERP Systems using Artificial Intelligence (ODSCM-ERPAI) method. The proposed ODSCM-ERPAI technique depends upon the optimization algorithm and DL-based prediction process for digital SCM. To achieve this, the ODSCM-ERPAI system originally completes data pre-processing to measure the input signals into a uniform format. Next, the Bi-LSTM method is used for the prediction process with the inclusion of an improved grey wolf optimization (IGWO) algorithm as a hyperparameter optimizer. To exhibit the improved performance of the ODSCM-ERPAI method, an extensive range of experiments are performed and the outcomes are inspected under various features.

2. Related Works

ElMadany et al. [11] developed a presented system to how to utilize ML in the production component of ERP systems. This method studied a new effort to facilitate an ERP system to create a semi-automatic or automatic decision in crucial problems in production. The presented technique is utilized for suggesting a novel fusion of product raw materials by utilizing ML. Khan et al. [12] handle how the SCM of a Distribution firm was enhanced by utilizing the ERP System. Effective SCM has an important role in placing the company at competitive benefit & improves the company production. SCM is the plan that goals for reducing the costs & improving the satisfaction of consumers. ERP offers a quality system, system usage, and consumer satisfaction. It supports superior planning, and decision-making and raises the complete performance of the organization. Bataineh et al. [13] studied the relationship among sustainable and digital supply chain in this case the ERP method and company proficiency of SCM. 33 responders from e-commerce companies agreed to participate in the data gathering method of research, the assumed relationships are studied by utilizing SEM.
Yan and Ramayah [14] introduce an SCM benefit evaluation system when executing the ERP system. This technique begins from the 2 features of ERP quantitative income and execution cost, which creates the evaluation index system of SCM benefit, and then normalizes every index and creates the evaluation system of enterprise SCM aid for ERP execution, and eventually attains the evaluation score in the ratio form of quantifiable income to ERP execution cost. Akbar and ŞİMŞEK [15] discovered the NN application and DL methods to improve streamline operations, and decision-making processes and expose useful information in the IT supply chain sales of medical devices. By levering innovative predictive and analytics modeling, organizations could obtain a better understanding of market tendencies, operational performance, and consumer preferences, allowing them to create informed strategic decisions and drive sustainable development. Gołąbek et al. [16] intended to create a platform for handling the structure of a particular company regarding the products and processes by utilizing AI. The system's improvement is based on new data analysis solutions, visualization, and the optimization of a product's life phases, aiding in monitoring technological and logistic processes with techniques of classifying and identifying the products in real-time. A

combined ecosystem has been produced by detecting products and components; this solution enables the constant monitoring of the quality and product status at each step of an intelligent supply chain, processes in real-time and adjusting plans, and allows the management of product versions in the distribution and manufacturing methods.

3. Proposed Models

In this article, we have projected an ODSCM-ERPAI method. The presented ODSCM-ERPAI technique involves data preprocessing, prediction process, and hyperparameter tuning process. Fig. 2 represents the entire procedure of the ODSCM-ERPAI model.

3.1. Data Preprocessing

At first, the presented ODSCM-ERPAI technique originally completes data pre-processing to measure the input signals into a uniform format. Min-max normalization measures data in an exact range, normally 0 to 1 [17]. In ERP systems, this method is employed to normalize values through dissimilar components, certifying reliability in data analysis and processing. By regularizing inputs such as sales figures or inventory counts, the ERP method can more efficiently incorporate and equate various datasets. This technique aids in enhancing decision-making and operational efficacy.

3.2. Prediction Method

Then, the Bi-LSTM model is used for the prediction process. LSTM is certainly a unique type of Recurrent Neural Network (RNN), which deals with definite problems in conventional RNNs like gradient vanishing, gradient explosion, and short memory time, by embracing a chained forward propagation framework [18]. The LSTM consists of 3 gates such as forget, input, and output gates. These gates together permit the LSTM to efficiently remember and learn data over long series, thereby alleviating the restrictions of classical RNNs. Its components are explained in detail below.

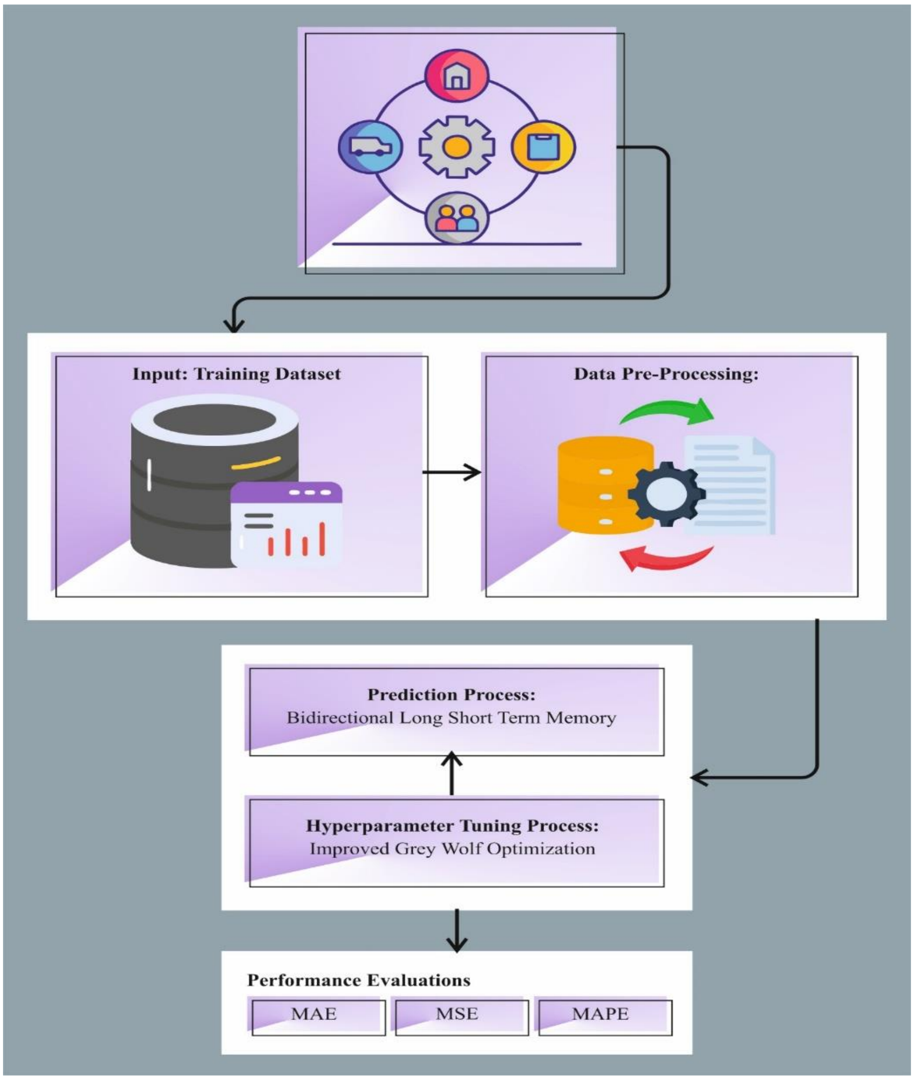

Fig. 2. Workflow of ODSCM-ERPAI model

The forget gate work is to define whether to remove the state of cell data in the preceding moment and which data wants to be remembered from the present cell. Its mathematical procedure is signified in Eq. (1)

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

Here, h_{t-1} denotes a preceding moment output, x_t means an input at the present moment, w_f and b_f represents weight and bias matrices, respectively, σ refers to the activation function of Sigmoid, and f_t means an output. The input gate is highly responsibility for making the data to be upgraded. Initially, it defines what data to be upgraded over Sigmoid and then produces the value of the candidate memory state $\overline{C_t}$ at the present moment overtan$h$, and lastly computes the upgraded state of cell C_t By multiplying the state of cell C_{t-1} from the preceding moment by the vector of forgetting point-wise. The mathematical computation of this procedure is given in Eqs. (2)-(4).

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$
$$\overline{C_t} = \tanh(W_c[h_{t-1}, x_t] + b_C) \quad (3)$$
$$C_t = f_t C_{t-1} + i_t \overline{C_t} \quad (4)$$

Here, W_i and b_i denotes input gate weight and bias matrices, respectively; W_c and b_C represents weight matrices of LSTM unit, correspondingly.
The output gate gets the primary output 0_t over sigmoid, and then gets the last output outcome h_t by multiplying the results obtained from the Sigmoid and tanh layers pair-wise. Its formulation is revealed in Eqs. (5) and (6).

$$\mathrm{o}_t = \sigma(W_\mathrm{o}[h_{t-1}, x_t] + b_\mathrm{o}) \quad (5)$$
$$h_t = o_t \tanh(C_t) \quad (6)$$

Here, b_0 and W_0 denotes output gate of bias and weight matrices, respectively. Bi-LSTM includes a reverse LSTM layer to network of LSTM for handling reverse data. The forward LSTM was highly responsibility for gaining the historical data of input series, and the reverse LSTM was answerable for attaining the upcoming data of input series. So, BiLSTM can well enhance long-term dependency issues, mine data features, and enhance accuracy and prediction.
The hidden layer (HL) h_t in every Bi-LSTM system at every level is made of the forward output and reverse HL and an input extent x_t at the present moment. The procedure of HL at every level is mentioned below in mathematical form:

$$\vec{h}_\mathrm{t} = LSTM\left(x_t, \vec{h}_{t-1}\right) \quad (7)$$
$$\overleftarrow{h}_t = LSTM\ \left(x_t, \overleftarrow{h}_{t+1}\right) \quad (8)$$
$$y_t = w_{\overrightarrow{hy}} \vec{h}_\mathrm{t} + w_t \overleftarrow{h}_t + b_y \quad (9)$$

Here, $\vec{h}_t$ and $\overleftarrow{h}_t$ signify the HL output of moments $t-1$ and $t+1$, $\vec{h}_t$ and $\overleftarrow{h}_t$ signify the HL output at tth moment, y_t means an output of Bi-LSTM, $w_{\overrightarrow{hy}}$ and $w_{\overleftarrow{h}y}$ denotes the weight of connection from forward and reverse LSTM to the output layers, respectively, b_y signifies bias.

3.3. Hyperparameter Tuning Process

Furthermore, the presented ODSCM-ERPAI method uses the IGWO algorithm as a hyperparameter optimizer. GWO is a swarm intellect-based optimizer model, which represents the classified social and structure movement of grey wolf groups [19]. Stimulated by the greedy behavior, the GWO model separates them into 4 classes such as α, β, δ, and ω, which signify numerous hierarchical layers in the wolf groups and pretend the leadership order and chasing device of grey wolf's. During the GWO model, latent solutions in the space of the problem were preserved as individuals in a compact of grey wolf's, where their behaviors of cooperative and competitive pretend the searching procedure for solution. During the complete searching procedure, the alpha wolf (α) with the finest fitness rank mains the activities, whereas the wolf's with the 2nd (β) and 3rd (δ) finest fitness positions help the alpha wolf in directing the group, and the residual wolf's upgrade their locations dependent upon them. The powers of GWO include the least parameters and a unique performance of converge. However, due to the chasing conduct of wolves, it frequently mains to reduced converge velocity in future phases, and the group leader will not reliably conquer the global optimum position, tasks affecting to local optimizer and other difficulties can quickly visible during the iterative procedure. So, the ZGWO model has been developed with the subsequent improvements. The accurate calculation is given as follows:

$$X_i = a \times X_{i-1} \times (1 - X_{i-1}) \quad (10)$$

Here, a denotes the control parameter, which defines the development of logistic mapping. In this research work, the a value is fixed to 4. i signifies existing iteration count When attaining the population data, reverse learning was executed. Every wolf location was resolved in reverse by utilizing the below-mentioned equation:

$$\overline{X_i} = \lambda \times (lb_i + ub_i) - X_i, \quad (11)$$

Whereas, lb_i and ub_i denotes the lower and upper bound values of X_i, respectively. Whereas λ refers to the randomly generated number within an interval of $(0\ and\ 1)$. Afterward, the arbitrary backpropagation (BP) learning procedure, the subsequent population was equated by the initially built solution space, and locations with a greater value of fitness were kept to generate a novel population.

This research paper presents an operator of Cauchy variation that is combined into the model's iteration procedure, then the GWO model is inclined to early convergence and local optimal creation. Using random perturbations to the alpha wolf's location upsurges the model range, enabling a local area to search and helping in finding of possible optimum solution. The enhanced local search ability creates it simpler for model to turn from the local optimal and also it simplifies the global search that hastily converges to the optimum solution's locality. The present optimum solution was changed utilizing the below-mentioned expression:

$$P_{new\_best} = P_{best\_i} + P_{best\_i} \times C(0,1) \quad (12)$$

Here, $C(0,1)$ refers to the standard Cauchy distributed randomly generated number. P_{best_i} denotes the existing optimum solution. While equating the value of fitness of the attained novel solution to the original optimum solution, the novel solution verifies that effective than the existing one, so the global optimum solution was upgraded to imitate the novel solution; if not, it remains similar.

For enhancing the capability for local search, an end of population substitute device is comprised in the population location upgrade stage simultaneously. The wolf's fitness was ranked from minimum to maximum, while the individuals with the lowest 20% were considered lower and wanted to be substituted. The other wolf's locations are retained, and novel locations are formed in their neighborhood dependent upon the head wolf's location as an ordinary. The below-mentioned formulation is employed to upgrade the ith wolf's location:

$$X_i = \begin{cases} \dfrac{x + x + X_3}{3}, i < P \times 0.8 \\ P_{best\_i} + r, other \end{cases} \quad (13)$$

Wherein, x_1, x_2 and x_3 denotes the location vectors attained dependent upon the alpha, beta, and delta wolf's correspondingly; r signifies the randomly generated number in the range of [-2, 2] employed to control the novel wolf location; P refers to the size of the population.

In this study, the IGWO is used to identify the hyperparameter convoluted in the BiLSTM method. The MSE is examined the objective function and described below.

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \quad (14)$$

Where M and L denote the resultant value of layer and data respectively, y_j^i and d_j^i denotes the achieved and correct magnitudes for j^{th} unit from the resulting layer of network in time t respectively.

4. Performance Analysis

This part inspects the performance study of the ODSCM-ERPAI method using a benchmark dataset [20]. Fig. 3 portrays the correlation matrix generated by the ODSCM-ERPAI method. The results state that the ODSCM-ERPAI technique has an accurate prediction of all class labels precisely.

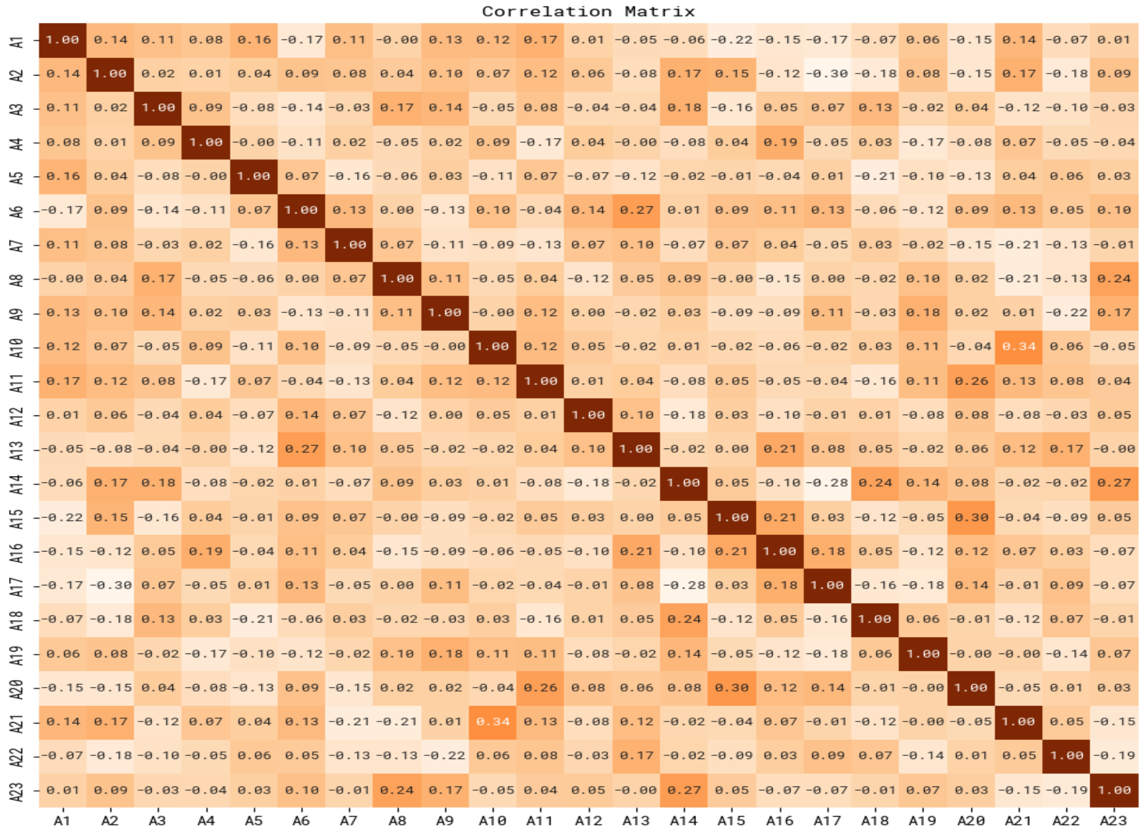

Fig. 3. Correlation Matrix of ODSCM-ERPAI technique

Fig. 4 allocates a Supply Chain study on the actual vs predicted ODSCM-ERPAI methodology. Similarly, it is recognized that the variance among the actual and predicted values can be calculated at a minimum.

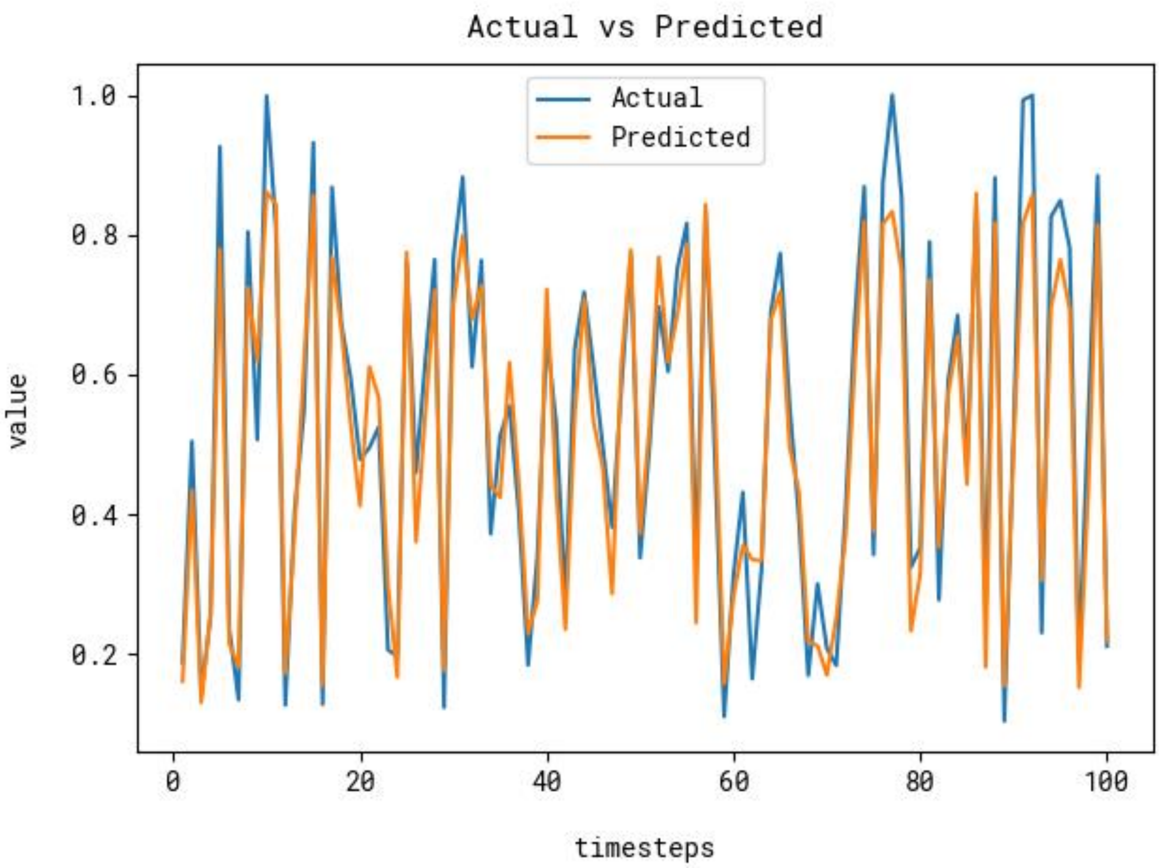

Fig. 4. SupplyChain Result Analysis for Actual vs Predicted ODSCM-ERPAI method

Table 1 and Fig. 5 imply the classifier results of the ODSCM-ERPAI system with different metrics. The outcomes inferred that the ODSCM-ERPAI approach has gained MSE of 0.005. Also, the ODSCM-ERPAI model has attained MAE of 0.061. Ultimately, the ODSCM-ERPAI method has reached MAPE of 0.145.

Table 1 Classifier outcomes of ODSCM-ERPAI technique with distinct metrics

Metrics	Values
MSE	0.005
MAE	0.061
MAPE	0.145

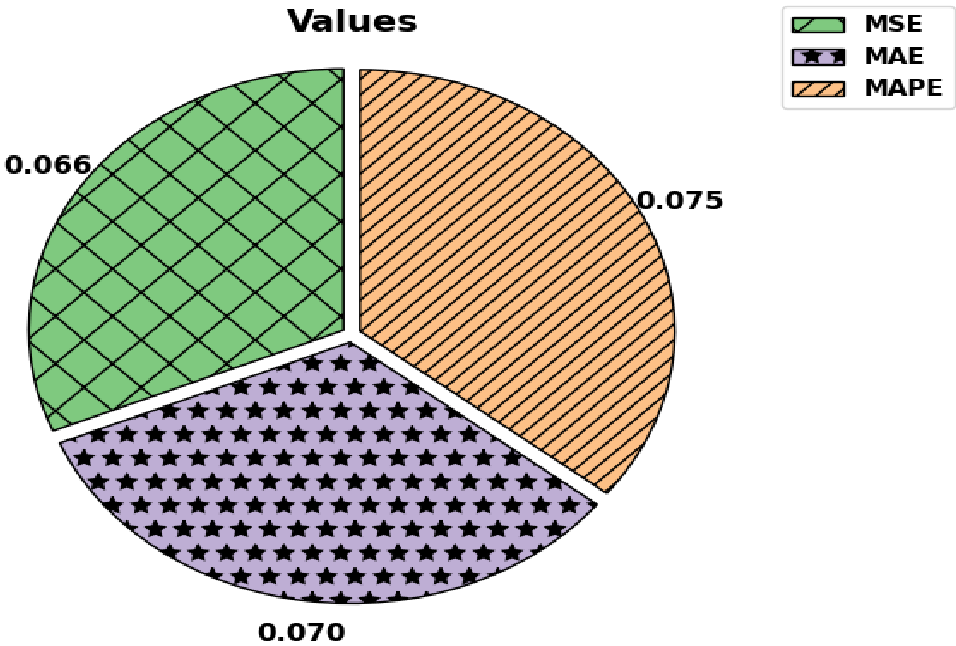

Fig. 5. Average of ODSCM-ERPAI technique with distinct metrics

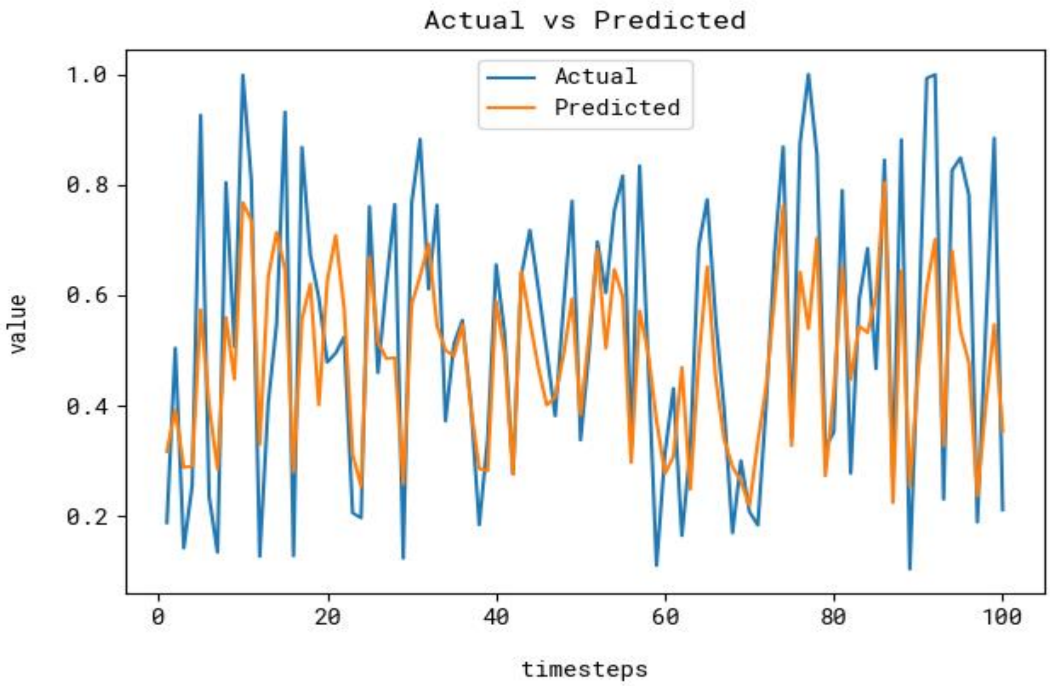

Fig. 6. SupplyChain Result Analysis for Actual vs Predicted under Epoch 25

Fig. 6 demonstrates the predicted supply chain result for the predicted vs actual ODSCM-ERPAI model on epoch count 25. This figure illustrates that the ODSCM-ERPAI approach correctly predicted the Supply Chain result. It is also observed that the predicted values by the ODSCM-ERPAI methodology are nearer to the actual values.
Fig. 7 displays the predicted supply chain result for the actual vs predicted ODSCM-ERPAI method on epoch count 50. This figure points out that the ODSCM-ERPAI system accurately predicted the Supply Chain result. It is also noted that the predicted values by the ODSCM-ERPAI process are adjacent to the actual values.

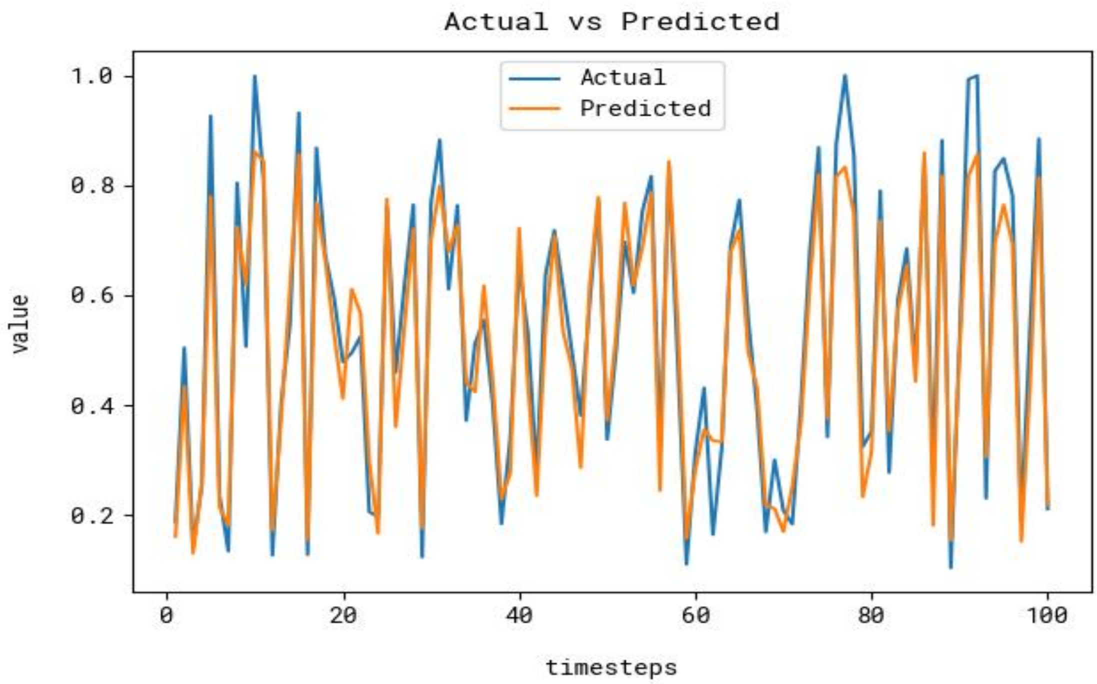

Fig. 7. SupplyChain Result Analysis for Actual vs Predicted under Epoch 50

Fig. 8 states the supply chain result for the loss graph of the ODSCM-ERPAI system under epoch count 25. The loss values are computed throughout 0-25 epoch counts. It is depicted that the training values indicate a lowering trend, informing the ability of the ODSCM-ERPAI approach to balance a trade-off between generalization and data fitting. The constant decrease in loss values also promises the greater performance of the ODSCM-ERPAI technique and tunes the prediction outcomes in time.

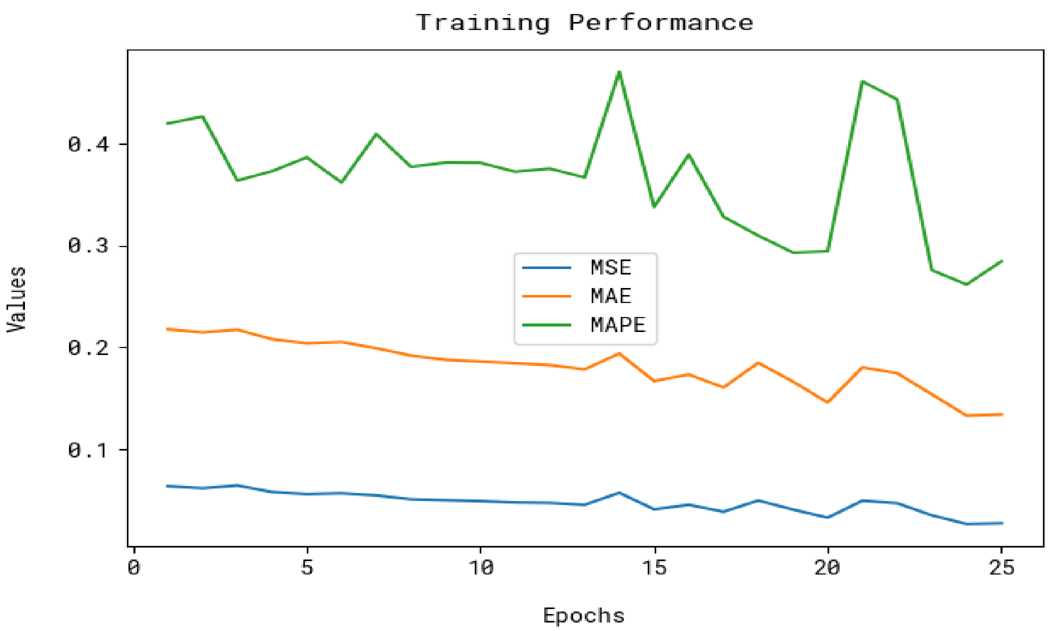

Fig. 8. SupplyChain Result Analysis for Loss Graph under Epoch 25

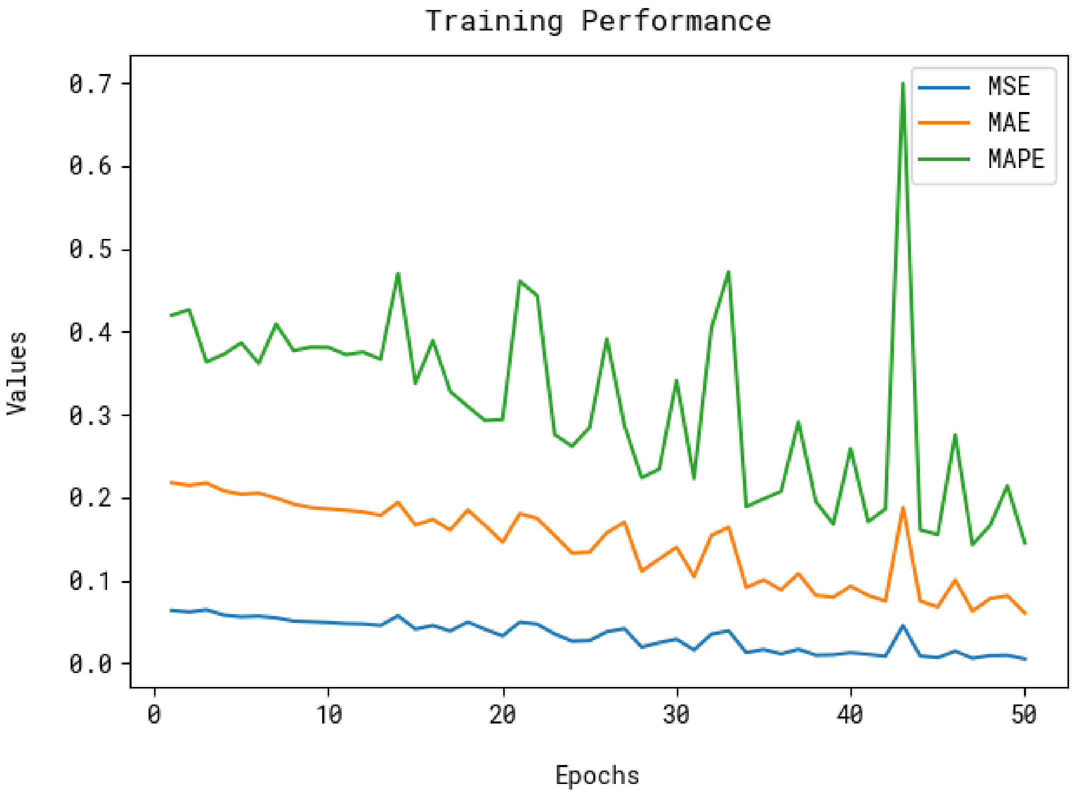

Fig. 9. SupplyChain Result Analysis for Loss Graph under Epoch 50

Fig. 9 demonstrates the supply chain result for the loss graph of ODSCM-ERPAI model under epoch count 50. The loss values are computed for 0-25 epoch counts. It is displayed that the training values described a reducing trend, reporting the proficiency of the ODSCM-ERPAI technique in balancing a trade-off between generalization and data fitting. The consistent lowering in loss values as well as assurances of the better performance of the ODSCM-ERPAI methodology and tuning the prediction outcomes on time.
To indicate the efficiency of the ODSCM-ERPAI method, a complete comparative study was performed in Table 2 and Fig. 10. The stimulated values inferred that the ODSCM-ERPAI method has improved performances under MSE. The GoogLeNet method has shown worse performances with a greater value MSE of 0.021. Simultaneously, the MobileNetV2 method has gained a somewhat lesser MSE of 0.018. In the meantime, the RF and SVM approaches have represented nearer values MSE of 0.013 and 0.008, correspondingly. However, the ODSCM-ERPAI system outcomes in better performance with the lowest value of MSE of 0.005.

Table 2 MSE outcome of ODSCM-ERPAI technique with existing approaches

Method	MSE
ODSCM-ERPAI	0.005
SVM Model	0.008
Random Forest	0.013
MobileNetV2	0.018
GoogLeNet	0.021

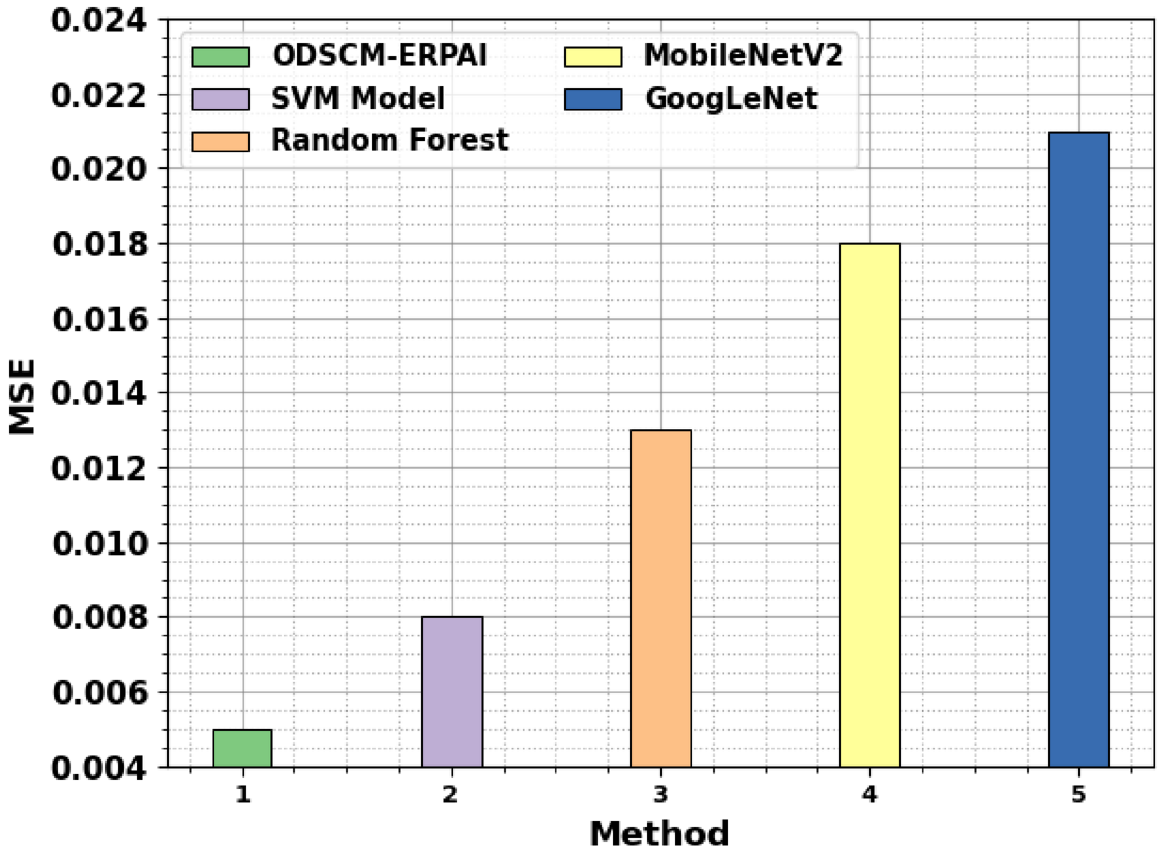

Fig. 10. MSE outcome of ODSCM-ERPAI technique with existing approaches

5. Conclusion

In this study, we have designed an ODSCM-ERPAI method. The presented ODSCM-ERPAI technique depends upon the optimization algorithm and DL-based prediction process for digital SCM. To accomplish this, the ODSCM-ERPAI technique originally completes data pre-processing to measure the input signals into a uniform format. Then, the Bi-LSTM model is used for the prediction process with the inclusion of IGWO algorithm as a hyperparameter optimizer. To exhibit the improved performance of the ODSCM-ERPAI method, an extensive range of experiments were performed and the results are inspected under several features. The experimental outcomes reported the enhanced outcomes of the ODSCM-ERPAI model over the other techniques.

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