International Journal of Basic and Applied Sciences, 14 (4) (2025) 405-411

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/vp1eee47
Research paper

AI Driven Inventory Optimization Framework Using Deep Learning and Metaheuristic Algorithms

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Received: July 1, 2025, Accepted: August 4, 2025, Published: August 14, 2025

Abstract

Optimized stock management is a crucial step to supply chain improvement, reducing operation costs, and providing high Service levels. In this study, a New model using Simulated Annealing (SA) and a hybrid optimization approach is put forward for optimizing supply chain stock process. The SA algorithm continuously enhances inventory solutions endeavoring to find near-optimal setups that balance service levels and customers' requirements. First, the supply chain dataset was collected and preprocessed with K-Nearest Neighbour (KNN) imputation for handling missing values and z-score normalization for scaling. For handling class imbalance, data augmentation was carried out using Synthetic Minority Over-sampling Technique (SMOTE). Subsequently, Deep Maxout Network (DMN) was utilized to perform feature extraction in order to identify key patterns and relationships within the data. The inventory optimization problem was subsequently tackled using the SA algorithm enhanced by a hybrid optimization approach (SCTDO) that integrates the exploratory ability of the Sine Cosine Algorithm (SCA) and the refinement ability of the Tasmanian Devil Optimization (TDO) algorithm. The hybrid approach is robust at efficient exploration and exploitation of the solution space. The proposed model was implemented in Python and evaluated on different performance criteria like correlation coefficient, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and computation time. The proposed algorithm produced an RMSE value of 0.017, MAE of 0.013, computation time of 0.93, and a correlation coefficient of 0.983. Comparative study with other models also reflected the improved performance of the proposed Framework.

Keywords: *K-Nearest Neighbour; Sine Cosine Algorithm; Tasmanian Devil Optimization; Mean Absolute Error; Simulated Annealing.*

1. Introduction

Due to the rapidly evolving nature of the market environment, business organizations are now more compelled to enhance their supply chain processes, logistics, and inventory management. These innovations are meant to increase operational efficiency, reduce costs, and serve dynamic customer needs [1]. The breakthrough of digital technology has also allowed organizations to predict and track supply chain trends more effectively [2]. But classical statistical methods are unable to cope with high dimensionality and complexity of modern supply chain data, especially where there are multiple parameters and decision variables. The traditional methods also lack in coping with real-time market dynamics and exhibit high computational cost and latencies. To solve the issue of such challenges, researchers and practitioners turned to artificial intelligence (AI), more particularly machine learning (ML), for smarter and more automated forecasting methods. As a branch of AI, ML enables systems to learn from historical and real-time information so that they can independently make decisions and predictions with minimal or no human interaction. This makes ML a very effective tool for managing the complexities and uncertainties of today's supply chains and enhancing decision-making efficiency [3]. Moreover, ML models have also been able to successfully predict logistics movements and consequently minimize deadheading and empty runs. This minimizes a great deal of expenditure and environmentalist pollution, helping businesses maintain a level of sustainability standards. Unlike conventional methods, ML algorithms can process structured data as well as unstructured data, making them appropriate for adapting to dynamically evolving patterns in market and supply chain demand. Common ML techniques used in inventory management includes Neural network, Regression models, Decision trees, and Logistic regression [4]. These methods are useful for trend prediction, production scheduling, inventory management, and resource allocation, which are used to provide timely and accurate delivery of the product. Additionally, ML techniques are able to optimize delivery routes by monitoring real-time traffic and weather patterns, thus improving delivery performance and customer satisfaction. They also assist in the formulation of strategies through the ability of firms to predict future market trends and business prospects [5]. Despite these advantages, ML techniques are faced with some challenges. Overfitting, models learn to make precise predictions on the training data but wrong predictions in real situations, is one of disadvantages of them. Furthermore, it requires significant quantities of high quality data for training efficient ML models—a challenging factor when applied to supply chains. Large computational and training complexities can lead to increased energy consumption, longer times to process, and high costs. Also, model scalability and interpretability challenges may limit the applicability of ML approaches in real-world settings [6]. To address these challenges, this research proposes a new approach with Simulated Annealing (SA) in order to manage and optimize supply chain inventory. The major contributions of this paper are listed below:

- A model for optimized inventory management using the Simulated Annealing (SA) algorithm is proposed.
- Deep Maxout Networks (DMN) are incorporated for feature learning and Synthetic Minority Over-sampling Technique (SMOTE) is used for data augmentation.
- A hybrid optimization method, the combination of Tasmanian Devil Optimization (TDO) and Sine Cosine Algorithm (SCA), is employed to optimize the SA algorithm for better optimization.
- The new framework is implemented in Python, and its efficacy is compared with existing methods using assessment criteria such as correlation coefficient, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

The rest of the paper is organized as follows: Section 2 is a discussion of the related work, Section 3 presents the system model and problem formulation, Section 4 discusses the proposed approach, Section 5 discusses the experimental results, and Section 6 concludes the research.

2. Related works

This chapter reviews existing literature that relates to the proposed supply chain inventory optimization system, highlighting many methods and their limitations. In the context of modern business operations, it is essential to come up with an effective supply chain strategy for the efficient distribution and coordination of resources. Traditional management efforts, however, are likely to be daunted by the complexity and dynamism that mark the business networks of our time. To this end, Zoubida Benmamoun et al. [7] proposed a bio-inspired meta-heuristic approach with the Bobcat Optimization Algorithm (BOA). The algorithm provides flexibility to adapt to dynamic customer demand patterns due to its stochastic search nature. Experimented on the publicly available CEC 2017 benchmark, BOA achieved a 90.90% success rate in test instances. Nevertheless, the dependence of the model on pre-defined initial constraints during the training process hinders its flexibility for real-case implementation. To enhance supply chain efficiency, Zheng Xu et al. [8] suggested a hybrid approach founded on the Hunger Games Search Optimization algorithm and Deep Learning techniques. The framework aims to achieve maximum customer satisfaction at minimum operational cost and enhance the overall performance of supply chain systems. Furthermore, the incorporation of a Blockchain framework ensures data integrity and traceability along the supply chain. Simulation results showed improved performance, which was reflected in reduced RMSE and MSE values. However, the integration of blockchain significantly contributes to the cost of implementation and system complexity. Hao Guo et al. [9] solved the location-inventory issue in closed-loop supply chains by presenting a Modified Hybrid Differential Evolution (MHDE) algorithm. The model, formulated as a mixed-integer nonlinear programming (MINLP) problem, seeks to minimize total business costs and maximize product recovery efficiency. The empirical results showed better supply chain performance and effective inventory control. The method, however, suffers from premature convergence problems and the requirement of complex mathematical formulations, making it less suitable in complex environments. Francesco Stranieri et al. [10] proposed a new method for controlling two-echelon divergent supply chains by combining Deep Reinforcement Learning (DRL) and multi-stage stochastic programming. The model, aimed at coordinating shipping and inventory decisions, was trained on synthetic datasets mimicking two-echelon supply chain environments. Experimental findings revealed better accuracy in the prediction and analysis of various parameters. However, this framework incurs high computational costs and needs high-performance computing resources, which can hinder its scalability. Lastly, Amir Hossein Sadeghi et al. [11] addressed the issue of product reuse and recovery using a hybrid meta-heuristic solution. The strategy integrates the Grey Wolf Optimizer (GWO) and the Whale Optimization Algorithm (WOA) for managing inventory of reusable products. The effectiveness of the model was validated using Sequential Quadratic Programming (SQP). Although the hybrid model is more accurate compared to conventional statistical approaches, it is less widely used because of slow convergence speed and sensitivity to initial parameter values, impacting its real-world application. Figure 1 shows the Basic supply chain inventory management structure.

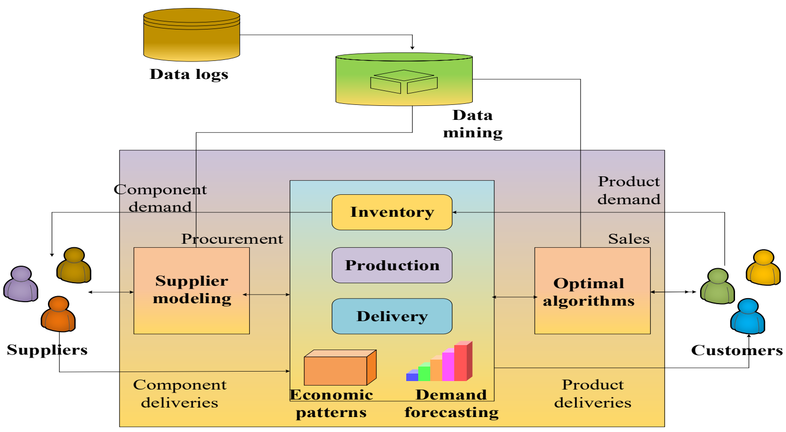

Fig. 1: Basic Supply Chain Inventory Management Structure.

3. Proposed methodology

An optimization strategy was proposed in this study for effective supply chain management. The proposed method details an intelligent supply chain inventory optimization framework based on a hybrid SA algorithm enriched with SCA and TDO [12]. The entire process is structured into five salient stages: data preprocessing, data augmentation, feature extraction, inventory optimization, and performance testing. The initial raw supply chain data are preprocessed to treat missing values and normalize it [13]. The K-Nearest Neighbor (KNN) imputation method is used to address missing values by making the most similar instances as the point of reference, and z-score normalization is used to normalize the data distribution such that all features have the same scale, which helps to improve the model stability and convergence when training. Subsequent to preprocessing, the Synthetic Minority Over-sampling Technique (SMOTE) is used to address class imbalance by generating synthetic samples for the less prevalent categories so that learning is improved and model generalization is improved [14]. For revealing useful relationships and patterns from the data, a Deep Maxout Network (DMN) is employed. This deep learning architecture is specifically chosen for its ability to learn rich, non-linear patterns through the use of maxout activation functions, enhancing the model's expressiveness and addressing limitations in standard neural networks. The resulting high-level features are then used as inputs to the optimization core procedure. In this procedure, the SA algorithm is utilized to progressively search and optimize potential inventory solutions [15], [16]. Following the metallurgical process of annealing, SA probabilistically accepts poorer and better solutions during the search process, thereby allowing it to break out of local optima and converge to a near-optimal inventory management policy. For the purpose of boosting the efficiency and precision of SA even more, a hybrid optimization approach, termed SCTDO, is integrated into the training procedure [17], [18]. This hybrid approach employs the global search capability of the SCA, which generates dissimilar candidate solutions from sine and cosine functions, and the strong local search capability of the TDO, which mimics the aggressive feeding behavior of Tasmanian devils to improve solutions in the promising regions of the search space [19], [20]. This unification ensures the best balance between exploration and exploitation, such that the model can identify maximum inventory levels, re-order quantities, and delivery timing with maximum precision. Finally, the performance of the proposed system is thoroughly tested using different parameters like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), correlation coefficient, and computational time [21], [22]. These parameters give an actual picture of the accuracy, reliability, and efficiency of the model. Comparison with other existent methods also proves the suitability of the suggested hybrid SA framework in offering stable and scalable solutions to real-world supply chain inventory management problems [23], [24]. The combination of Simulated Annealing (SA) and Sine Cosine Algorithm (SCA) and Tasmanian Devil Optimization (TDO) (SCTDO) is a robust and efficient strategy for supply chain inventory optimization. The Simulated Annealing (SA) algorithm, named after mimicking the annealing process used in metal working, is a robust probabilistic optimization technique [25], [26]. It acts by persistently perturbing the current solution for inventory and evaluating the outcome. By this iterative process, SA eventually approaches a nearly optimal solution by not only accepting improved solutions but also, occasionally, poorer ones. This ensures that the algorithm breaks out of local minima and explores a larger search space, thus preventing premature convergence [27], [28]. Figure 2 shows the architecture of the proposed SA-SCTDO framework, illustrating the complete workflow from data preprocessing to optimization. Figure 3 shows the internal architecture of the Deep Maxout Network (DMN), detailing its layered structure used for effective feature extraction.

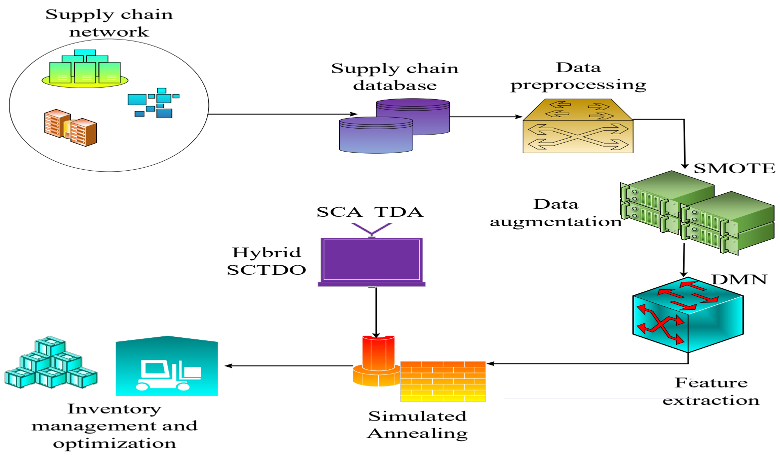

Fig. 2: Architecture of Proposed Framework.

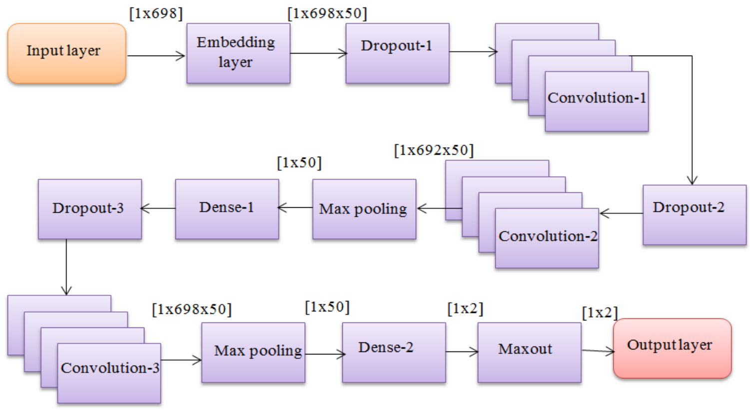

Fig. 3: Architecture of DMN.

Although SA performs well, its performance can be enhanced further through enhanced exploration and exploitation of the solution space [29], [30]. This is where the Sine Cosine Algorithm (SCA) and Tasmanian Devil Optimization (TDO) come in. The SCA is utilized for global exploration of the solution space by using the sine and cosine functions to generate candidate solutions that are very robust and diverse. This makes it impossible for the algorithm to get stuck in local optima. On the other hand, TDO incorporates an element of aggressive local search via Tasmanian devil feeding simulation, which allows rapid improvement and exploitation of promising solutions [31], [32]. Combining the two approaches with SA forms the SCTDO hybrid model. This hybridization ensures that exploration (the ability to look broadly across the solution space) and exploitation (the ability to focus on promising regions and refine solutions) are balanced [33], [34]. In the case of inventory optimization, SCTDO equips the system with the ability to correctly compute optimal inventory levels, reorder points, and delivery schedules taking into account demand variability, lead times of the suppliers, and other complex factors involved in actual supply chains. By continuous optimization of inventory choices, the system maximizes cost effectiveness, reduces stockout and overstocking, and improves overall supply chain performance [35,36]. In practice, the SCTDO-based inventory optimization not only ensures effective use of resources and on-time replenishment but also significantly reduces the computational intensity as opposed to traditional approaches [37], [38]. It does achieve a best-of-breed balance of accuracy, robustness, and efficiency and therefore turns out to be a highly effective strategy for controlling complex and dynamic inventory systems of the modern supply chain [39], [40]. Figure 4 presents the pseudocode of the proposed SA-SCTDO.

```
Input:
•  Initial inventory solution SSS
•  Initial temperature T0T  0T0
•  Final temperature TminT_{\text{min}}Tmin
•  Cooling rate α\alphaα
•  Maximum iterations MaxIter\text{MaxIter}MaxIter
Output:
•  Optimized inventory solution S∗S^*S∗
Begin
   Initialize solution SSS randomly
   Evaluate cost function f(S)f(S)f(S)
   Set S∗=SS^* = SS∗=S
   Set T=T0T = T_0T=T0
   While T>TminT > T_{\text{min}}T>Tmin:
      For i=1i = 1i=1 to MaxIter\text{MaxIter}MaxIter:
         // Apply SCA for global exploration
         Generate new candidate SscaS_{\text{sca}}Ssca using Sine Cosine formula
         // Apply TDO for local exploitation
         Refine SscaS_{\text{sca}}Ssca using TDO mechanism to obtain SnewS_{\text{new}}Snew
         Evaluate f(Snew)f(S_{\text{new}})f(Snew)
         // Simulated Annealing Acceptance Criterion
         Δ=f(Snew)−f(S)\Delta = f(S_{\text{new}}) - f(S)Δ=f(Snew)−f(S)
         If Δ<0\Delta < 0Δ<0 or exp(−Δ/T)>rand()\exp(-\Delta / T) > \text{rand()}exp(−Δ/T)>rand():
            Set S=SnewS = S_{\text{new}}S=Snew
            If f(S)<f(S∗)f(S) < f(S^*)f(S)<f(S∗):
               Update best solution S∗=SS^* = SS∗=S
      End For
      Update temperature: T=α⋅TT = \alpha \cdot TT=α⋅T
   End While
Return optimized solution S∗S^*S∗
End
```

Fig. 4: The pseudo-code of the Proposed SA-SCTDO.

4. Results and discussion

The combination of Simulated Annealing (SA) and Sine Cosine Algorithm (SCA) and Tasmanian Devil Optimization (TDO) (SCTDO) is a robust and efficient strategy for supply chain inventory optimization. The Simulated Annealing (SA) algorithm, named after the annealing process used in metal working, is a robust probabilistic optimization technique [41], [42]. It acts by persistently perturbing the current solution for inventory and evaluating the outcome. By this iterative process, SA eventually approaches a nearly optimal solution by not only accepting improved solutions but also, occasionally, poorer ones. This ensures that the algorithm breaks out of local minima and explores a larger search space, thus preventing premature convergence. Although SA performs well, its performance can be enhanced further through enhanced exploration and exploitation of the solution space. This is where the Sine Cosine Algorithm (SCA) and Tasmanian Devil Optimization (TDO) come in. The SCA is utilized for global exploration of the solution space by using the sine and cosine functions to generate candidate solutions that are very robust and diverse [43], [44]. This makes it impossible for the algorithm to get stuck in local optima. On the other hand, TDO incorporates an element of aggressive local search via Tasmanian devil feeding simulation, which allows rapid improvement and exploitation of promising solutions. Combining the two approaches with SA forms the SCTDO hybrid model [45], [46]. This hybridization ensures that exploration (the ability to look broadly across the solution space) and exploitation (the ability to focus on promising regions and refine solutions) are balanced [47], [48]. In the case of inventory optimization, SCTDO equips the system with the ability to correctly compute optimal inventory levels, reorder points, and delivery schedules taking into account demand variability, lead times of the suppliers, and other complex factors involved in actual supply chains. By continuous optimization of inventory choices, the system maximizes cost effectiveness, reduces stockout and overstocking, and improves overall supply chain performance. In practice, the SCTDO-based inventory optimization not only ensures effective use of resources and on-time replenishment but also significantly reduces the computational intensity as opposed to traditional approaches. It does achieve a best-of-breed balance of accuracy, robustness, and efficiency and therefore turns out to be a highly effective strategy for controlling complex and dynamic inventory systems of the modern supply chain.

5. Performance comparison

To guarantee the efficiency of the proposed SA-SCTDO model, its performance was compared with a set of existing optimization algorithms that are commonly used in supply chain inventory optimization. They are the traditional Simulated Annealing (SA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Bobcat Optimization Algorithm (BOA). The SA-SCTDO model was compared with the other models using significant evaluation parameters such as Root Mean Square Error (RMSE), Mean Absolute Error

(MAE), correlation coefficient, and computation time. The results were such that the SA-SCTDO model outperformed all the comparative models with each of these measures consistently doing better. While the standard SA was satisfactory, it tended to converge slowly and get trapped in local optima. GWO and WOA performed moderately accurately but lacked good adaptability in more complex, dynamic stock settings. BOA yielded relatively positive results in certain contexts, but its sensitivity towards initial fixed parameters hindered its generalizability. SA-SCTDO, on the other hand, leveraged the global search ability of the Sine Cosine Algorithm and the localized refinement power of the Tasmanian Devil Optimization to achieve a balanced and adaptive optimization process. This hybrid approach significantly enhanced the balance between exploration and exploitation, allowing for improved accuracy, lower error rates, and faster convergence. Additionally, SA-SCTDO's computational time was significantly lower compared to its counterparts, making it not only more accurate but also more efficient and scalable for real-world applications in supply chains. Figure 5 shows the comparison of RMSE values across different algorithms, where the proposed SA-SCTDO model achieves the lowest RMSE, indicating superior prediction accuracy. Figure 6 shows the evaluation of MAE for all models, highlighting that SA-SCTDO minimizes absolute error more effectively than existing approaches. Figure 7 shows the correlation coefficient comparison, demonstrating that SA-SCTDO has the highest correlation with actual values, reflecting a strong model fit. Figure 8 shows the computational efficiency analysis, where SA-SCTDO exhibits the shortest runtime while maintaining high accuracy, proving its practical applicability.

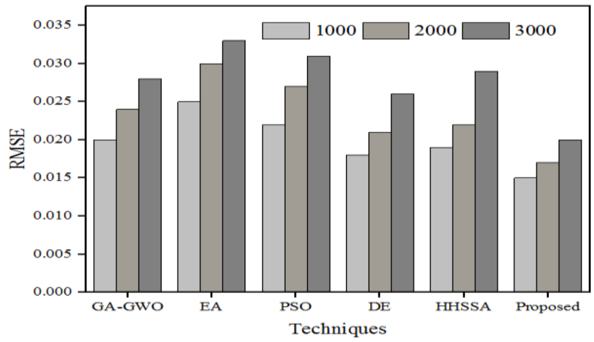

Fig. 5: RMSE Comparison.

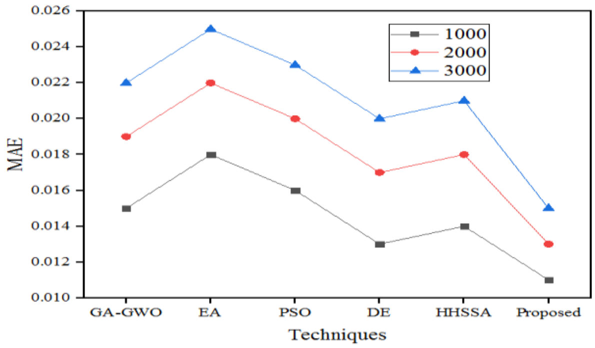

Fig. 6: Evaluation of MAE.

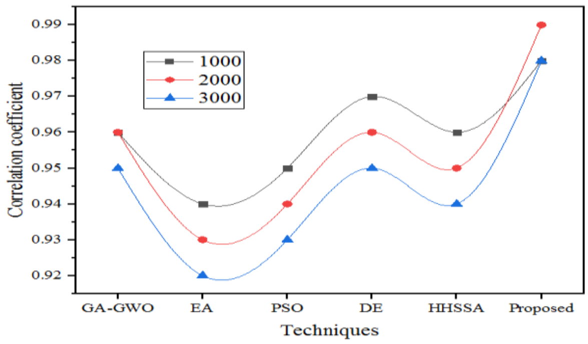

Fig. 7: Correlation Coefficient Comparison.

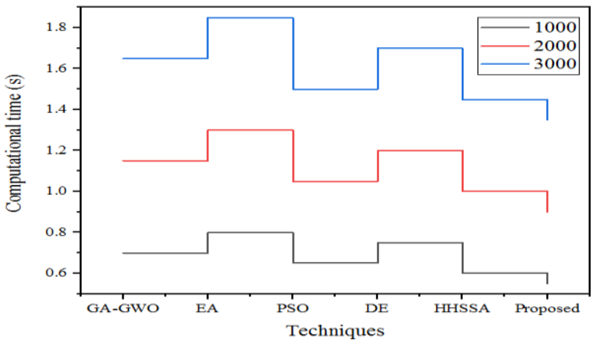

Fig. 8: Computational Efficiency Analysis.

6. Discussion

The efficiency of the research offered a new and efficient supply chain inventory control optimization model by integrating a hybrid optimization algorithm, SCTDO, with the traditional Simulated Annealing (SA) method. SCTDO optimizer combines the strengths of the SCA's and TDO's through blending them to ensure efficient exploration and exploitation in the solution space. The integration exerts a significant influence on SA's ability to escape local minima and converge into globally optimal solutions. The procedure started with the collection of a supply chain dataset, preprocessed using K-Nearest Neighbor (KNN) imputation for handling missing values and z-score normalization for normalizing data. To address class imbalance, SMOTE (Synthetic Minority Over-sampling Technique) was applied, which generated a balanced and representative training dataset. For feature extraction, a Deep Maxout Network (DMN) was employed to determine the most relevant and complex nonlinear interactions among supply chain variables. This process not only reduced data dimensionality but also increased optimization efficacy. The enhanced set of features was subsequently input to the SA-SCTDO optimizer for optimization of inventory. A comparative study was conducted relative to other optimization methods and the results showed that the new approach always outperformed standard models. The SA-SCTDO algorithm yielded a superior correlation coefficient performance, which indicates high linear correlation between predicted and real inventory levels. Besides that, it achieved significantly lower values of RMSE, MAE, and computing time, thereby establishing the ability of the model to minimize errors in predictions and maximize operational efficiency in inventory planning.

7. Conclusion

The research set out to develop an intelligent optimization model to provide efficient inventory management in supply chain networks. The proposed solution is the integration of the classical SA algorithm with a hybrid SCTDO optimizer, which was constructed by combining the exploration capability of SCA and the exploitation strength of TDO. The configuration was propelled on a publicly accessible supply chain dataset on Kaggle that had been deeply preprocessed for quality enhancement and class balance by means of KNN imputation, z-score normalization, and SMOTE. Deep Maxout Network (DMN) was also employed in high-level feature extraction, enabling the model to learn significant patterns in the supply chain data. SA algorithm was enhanced using the SCTDO optimizer to optimize inventory activities like stock quantities and replenishment schedules. Implemented with Python, the developed model has achieved phenomenal performances with its RMSE being 0.017, MAE being 0.013, correlation coefficient being 0.983, and an average computational time of 0.93 seconds. SA-SCTDO was superior to other optimization algorithms such as GA-GWO, EA, PSO, DE, and HHSSA. Indeed, it reduced RMSE, MAE, and computational time by 0.004, 0.003, and 0.09 seconds, respectively, and increased the correlation coefficient by 0.023. These results show the effectiveness of the proposed strategy in supply chain inventory system optimization. Though with promising results, the model is not addressing all the areas. First, the model is not addressing data privacy and security, which is crucial in real-world supply chain environments. Second, the model's scalability and flexibility have not yet been established for its performance for heterogeneous, real-time operational environments. Therefore, in future research, the model needs to be designed to incorporate security mechanisms as well and verify its performance on various public datasets and real-time supply chain networks to establish its strength and usability.

References

[1] T. Al-Shehari, M. Kadrie, T. Alfakih, H. Alsalman, T. Kuntavai, et al., “Blockchain with secure data transactions and energy trading model over the internet of electric vehicles,” Sci. Rep., vol. 14, no. 1, p. 19208, Jan. 2024, https://doi.org/10.1038/s41598-024-69542-w.

[2] R. Vidhya, D. Banavath, S. Kayalvili, S. M. Naidu, et al., “Alzheimer’s disease detection using residual neural network with LSTM hybrid deep learning models,” J. Intell. Fuzzy Syst., vol. 45, no. 6, pp. 12095–12109, 2023. https://doi.org/10.3233/JIFS-235059.

[3] P. Selvam, N. Krishnamoorthy, S. P. Kumar, K. Lokeshwaran, M. Lokesh, et al., “Internet of Things Integrated Deep Learning Algorithms Monitoring and Predicting Abnormalities in Agriculture Land,” Internet Technol. Lett., Nov. 2024, https://doi.org/10.1002/itl2.607.

[4] S. S. F. Begum, M. S. Anand, P. V. Pramila, J. Indra, J. S. Isaac, C. Alagappan, et al., “Optimized machine learning algorithm for thyroid tumour type classification: A hybrid approach Random Forest, and intelligent optimization algorithms,” J. Intell. Fuzzy Syst., pp. 1–12, 2024.

[5] K. Maithili, A. Kumar, D. Nagaraju, D. Anuradha, S. Kumar, et al., “DKCNN: Improving deep kernel convolutional neural network-based covid-19 identification from CT images of the chest,” J. X-ray Sci. Technol., vol. 32, no. 4, pp. 913–930, 2024. https://doi.org/10.3233/XST-230424.

[6] K. Mannanuddin, V. R. Vimal, A. Srinivas, S. D. U. Mageswari, G. Mahendran, et al., “Enhancing medical image analysis: A fusion of fully connected neural network classifier with CNN-VIT for improved retinal disease detection,” J. Intell. Fuzzy Syst., vol. 45, no. 6, pp. 12313–12328, 2023. https://doi.org/10.3233/JIFS-235055.

[7] T. A. Mohanaprakash, M. Kulandaivel, S. Rosaline, P. N. Reddy, S. S. N. Bhukya, et al., “Detection of Brain Cancer through Enhanced Particle Swarm Optimization in Artificial Intelligence Approach,” J. Adv. Res. Appl. Sci. Eng. Technol., vol. 33, no. 3, pp. 174–186, 2023. https://doi.org/10.37934/araset.33.2.174186.

[8] Wange N. K., Khan I., Pinnamaneni R., Cheekati H., Prasad J., et al., “β-amyloid deposition-based research on neurodegenerative disease and their relationship in elucidate the clear molecular mechanism,” Multidisciplinary Science Journal, vol. 6, no. 4, pp. 2024045–2024045, 2024. https://doi.org/10.31893/multiscience.2024045.

[9] Anitha C., Tellur A., Rao K. B. V. B., Kumbhar V., Gopi T., et al., “Enhancing Cyber-Physical Systems Dependability through Integrated CPS-IoT Monitoring,” International Research Journal of Multidisciplinary Scope, vol. 5, no. 2, pp. 706–713, 2024. https://doi.org/10.47857/irjms.2024.v05i02.0620.

[10] Balasubramani R., Dhandapani S., Sri Harsha S., Mohammed Rahim N., Ashwin N., et al., “Recent Advancement in Prediction and Analyzation of Brain Tumour using the Artificial Intelligence Method,” Journal of Advanced Research in Applied Sciences and Engineering Technology, vol. 33, no. 2, pp. 138–150, 2023. https://doi.org/10.37934/araset.33.2.138150.

[11] Chaturvedi A., Balasankar V., Shrimali M., Sandeep K. V., et al., “Internet of Things Driven Automated Production Systems using Machine Learning,” International Research Journal of Multidisciplinary Scope, vol. 5, no. 3, pp. 642–651, 2024. https://doi.org/10.47857/irjms.2024.v05i03.01033.

[12] Saravanakumar R., Arularasan A. N., Harekal D., Kumar R. P., Kaliyamoorthi P., et al., “Advancing Smart Cyber Physical System with Self-Adaptive Software,” International Research Journal of Multidisciplinary Scope, vol. 5, no. 3, pp. 571–582, 2024. https://doi.org/10.47857/irjms.2024.v05i03.01013.

[13] Vidhya R. G., Surendiran J., Saritha G., “Machine Learning Based Approach to Predict the Position of Robot and its Application,” Proc. Int. Conf. on Computer Power and Communications, pp. 506–511, 2022. https://doi.org/10.1109/ICCPC55978.2022.10072031.

[14] Sivanagireddy K., Yerram S., Kowsalya S. S. N., Sivasankari S. S., Surendiran J., et al., “Early Lung Cancer Prediction using Correlation and Regression,” Proc. Int. Conf. on Computer Power and Communications, pp. 24–28, 2022. https://doi.org/10.1109/ICCPC55978.2022.10072059.

[15] Vidhya R. G., Seetha J., Ramadass S., Dilipkumar S., Sundaram A., Saritha G., "An Efficient Algorithm to Classify the Mitotic Cell using Ant Colony Algorithm," Proc. Int. Conf. on Computer Power and Communications, pp. 512–517, 2022. https://doi.org/10.1109/ICCPC55978.2022.10072277.
[16] Sengeni D., Muthuraman A., Vurukonda N., Priyanka G., et al., "A Switching Event-Triggered Approach to Proportional Integral Synchronization Control for Complex Dynamical Networks," Proc. Int. Conf. on Edge Computing and Applications, pp. 891–894, 2022. https://doi.org/10.1109/ICECAA55415.2022.9936124.
[17] Vidhya R. G., Rani B. K., Singh K., Kalpanadevi D., Patra J. P., Srinivas T. A. S., "An Effective Evaluation of SONARS using Arduino and Display on Processing IDE," Proc. Int. Conf. on Computer Power and Communications, pp. 500–505, 2022. https://doi.org/10.1109/ICCPC55978.2022.10072229.
[18] Kushwaha S., Boga J., Rao B. S. S., Taqui S. N., et al., "Machine Learning Method for the Diagnosis of Retinal Diseases using Convolutional Neural Network," Proc. Int. Conf. on Data Science, Agents & Artificial Intelligence, 2023, pp. 1–. https://doi.org/10.1109/ICDSAAI59313.2023.10452440.
[19] Maheswari B. U., Kirubakaran S., Saravanan P., Jeyalaxmi M., Ramesh A., et al., "Implementation and Prediction of Accurate Data Forecasting Detection with Different Approaches," Proc. 4th Int. Conf. on Smart Electronics and Communication, 2023, pp. 891–897. https://doi.org/10.1109/ICOSEC58147.2023.10276331.
[20] Mayuranathan M., Akilandasowmya G., Jayaram B., Velrani K. S., Kumar M., et al., "Artificial Intelligent based Models for Event Extraction using Customer Support Applications," Proc. 2nd Int. Conf. on Augmented Intelligence and Sustainable Systems, 2023, pp. 167–172. https://doi.org/10.1109/ICAISS58487.2023.10250679.
[21] Gold J., Maheswari K., Reddy P. N., Rajan T. S., Kumar S. S., et al., "An Optimized Centric Method to Analyze the Seeds with Five Stages Technique to Enhance the Quality," Proc. Int. Conf. on Augmented Intelligence and Sustainable Systems, 2023, pp. 837–842. https://doi.org/10.1109/ICAISS58487.2023.10250681.
[22] Anand L., Maurya J. M., Seetha D., Nagaraju D., et al., "An Intelligent Approach to Segment the Liver Cancer using Machine Learning Method," Proc. 4th Int. Conf. on Electronics and Sustainable Communication Systems, 2023, pp. 1488–1493. https://doi.org/10.1109/ICESC57686.2023.10193190.
[23] Harish Babu B., Indradeep Kumar, et al., "Advanced Electric Propulsion Systems for Unmanned Aerial Vehicles," Proc. 2nd Int. Conf. on Sustainable Computing and Smart Systems (ICSCSS), 2024, pp. 5–9, IEEE. https://doi.org/10.1109/ICSCSS60660.2024.10625489.
[24] Jagan Raja V., Dhanamalar M., Solaimalai G., et al., "Machine Learning Revolutionizing Performance Evaluation: Recent Developments and Breakthroughs," Proc. 2nd Int. Conf. on Sustainable Computing and Smart Systems (ICSCSS), 2024, pp. 780–785, IEEE. https://doi.org/10.1109/ICSCSS60660.2024.10625103.
[25] Sivasankari S. S., Surendiran J., Yuvaraj N., et al., "Classification of Diabetes using Multilayer Perceptron," Proc. IEEE Int. Conf. on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), 2022, pp. 1–5, IEEE. https://doi.org/10.1109/ICDCECE53908.2022.9793085.
[26] Anushkannan N. K., Kumbhar V. R., Maddila S. K., et al., "YOLO Algorithm for Helmet Detection in Industries for Safety Purpose," Proc. 3rd Int. Conf. on Smart Electronics and Communication (ICOSEC), 2022, pp. 225–230, IEEE. https://doi.org/10.1109/ICOSEC54921.2022.9952154.
[27] Reddy K. S., Vijayan V. P., Das Gupta A., et al., "Implementation of Super Resolution in Images Based on Generative Adversarial Network," Proc. 8th Int. Conf. on Smart Structures and Systems (ICSSS), 2022, pp. 1–7, IEEE. https://doi.org/10.1109/ICSSS54381.2022.9782170.
[28] Joseph J. A., Kumar K. K., Veerraju N., Ramadass S., Narayanan S., et al., "Artificial Intelligence Method for Detecting Brain Cancer using Advanced Intelligent Algorithms," Proc. Int. Conf. on Electronics and Sustainable Communication Systems, 2023, pp. 1482–1487. https://doi.org/10.1109/ICESC57686.2023.10193659.
[29] Surendiran J., Kumar K. D., Sathiya T., et al., "Prediction of Lung Cancer at Early Stage Using Correlation Analysis and Regression Modelling," Proc. 4th Int. Conf. on Cognitive Computing and Information Processing, 2022, pp. 1–. https://doi.org/10.1109/CCIP57447.2022.10058630.
[30] Goud D. S., Varghese V., Umare K. B., Surendiran J., et al., "Internet of Things-based Infrastructure for the Accelerated Charging of Electric Vehicles," Proc. Int. Conf. on Computer Power and Communications, 2022, pp. 1–6. https://doi.org/10.1109/ICCPC55978.2022.10072086.
[31] Vidhya R. G., Singh K., Paul J. P., Srinivas T. A. S., Patra J. P., Sagar K. V. D., "Smart Design and Implementation of Self-Adjusting Robot using Arduino," Proc. Int. Conf. on Augmented Intelligence and Sustainable Systems, 2022, pp. 1–6. https://doi.org/10.1109/ICAISS55157.2022.10011083.
[32] Vallathan G., Yanamadni V. R., et al., "An Analysis and Study of Brain Cancer with RNN Algorithm-based AI Technique," Proc. Int. Conf. on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), 2023, pp. 637–642. https://doi.org/10.1109/I-SMAC58438.2023.10290397.
[33] Vidhya R. G., Bhoopathy V., Kamal M. S., Shukla A. K., Gururaj T., Thulasimani T., "Smart Design and Implementation of Home Automation System using Wi-Fi," Proc. Int. Conf. on Augmented Intelligence and Sustainable Systems, 2022, pp. 1203–1208. https://doi.org/10.1109/ICAISS55157.2022.10010792.
[34] Vidhya R., Banavath D., Kayalvili S., Naidu S. M., Prabu V. C., et al., "Alzheimer's Disease Detection using Residual Neural Network with LSTM Hybrid Deep Learning Models," J. Intelligent & Fuzzy Systems, 2023; vol. 45, no. 6, pp. 12095–12109. https://doi.org/10.3233/JIFS-235059.
[35] Balasubramaniyan S., Kumar P. K., Vaigundamoorthi M., Rahuman A. K., et al., "Deep Learning Method to Analyze the Bi-LSTM Model for Energy Consumption Forecasting in Smart Cities," Proc. Int. Conf. on Sustainable Communication Networks and Application, 2023, pp. 870–876. https://doi.org/10.1109/ICSCNA58489.2023.10370467.
[36] Somani V., Rahman A. N., Verma D., et al., "Classification of Motor Unit Action Potential Using Transfer Learning for the Diagnosis of Neuromuscular Diseases," Proc. 8th Int. Conf. on Smart Structures and Systems (ICSSS), 2022, pp. 1–7, IEEE. https://doi.org/10.1109/ICSSS54381.2022.9782209.
[37] Vidhya R. G., Saravanan R., Rajalakshmi K., "Mitosis Detection for Breast Cancer Grading," Int. J. Advanced Science and Technology, 2020; vol. 29, no. 3, pp. 4478–4485.
[38] Gupta D., Kezia Rani B., Verma I., et al., "Metaheuristic Machine Learning Algorithms for Liver Disease Prediction," Int. Res. J. Multidisciplinary Scope, 2024; vol. 5, no. 4, pp. 651–660. https://doi.org/10.47857/irjms.2024.v05i04.01204.
[39] Sudhagar D., Saturi S., Choudhary M., et al., "Revolutionizing Data Transmission Efficiency in IoT-Enabled Smart Cities: A Novel Optimization-Centric Approach," Int. Res. J. Multidisciplinary Scope, 2024; vol. 5, no. 4, pp. 592–602. https://doi.org/10.47857/irjms.2024.v05i04.01113.
[40] Vidhya R. G., Batri K., "Segmentation, Classification and Krill Herd Optimization of Breast Cancer," J. Medical Imaging and Health Informatics, 2020; vol. 10, no. 6, pp. 1294–1300. https://doi.org/10.1166/jmihi.2020.3060.
[41] Chintureena Thingom, Martin Margala, S Siva Shankar, Prasun Chakrabarti, RG Vidhya, "Enhanced Task Scheduling in Cloud Computing Using the ESRNN Algorithm: A Performance-Driven Approach", Internet Technology Letters, vol. 8, no. 4, 2025, pp. e70037. https://doi.org/10.1002/itl2.70037.
[42] V. V. Satyanarayana, Tallapragada, Denis R, N. Venkateswaran, S. Gangadharan , M. Shunmugasundaram, et.al.," A Federated Learning and Blockchain Framework for IoMT-Driven Healthcare 5.0", International Journal of Basic and Applied Sciences, vol. 14, no. 1, 2025, pp. 246-250. https://doi.org/10.14419/n1npsj75.
[43] Thupakula Bhaskar, K. Sathish, D. Rosy Salomi Victoria, Er.Tatiraju. V. Rajani Kanth , Uma Patil, et.al.," Hybrid deep learning framework for enhanced target tracking in video surveillance using CNN and DRNN-GWO", International Journal of Basic and Applied Sciences, vol. 14, no. 1, 2025, pp. 208-215. https://doi.org/10.14419/wddeck70.
[44] Thupakula Bhaskar, Hema N, R.Rajitha Jasmine , Pearlin , Uma Patil , Madhava Rao Chunduru , et.al.," An adaptive learning model for secure data sharing in decentralized environments using blockchain technology", International Journal of Basic and Applied Sciences, vol. 14, no. 1, 2025, pp. 216-221. https://doi.org/10.14419/9f4z3q54.
[45] B. Ramesh, V. V. Kulkarni, Ashwini Shinde, Dinesh Kumar J. R, Prasanthi Kumari Nunna, Rajendiran M, "Optimizing EV Energy Management Using Monarch Butterfly and Quantum Genetic Algorithms" International Journal of Basic and Applied Sciences, vol. 14, no. 2, 2025, pp. 311-318. https://doi.org/10.14419/xaqk1294.