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Supply Chain Optimization With Hybrid Particle Swarm Optimization And Xgboost

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Abstract

Forecasting and Distribution/Inventory planning are both critical for supply chain management for optimum service level management and cost reduction. However, the conventional techniques fail to address complex non-linear and dynamic requirements. In this study, we propose a hybrid PSO and XGBoost technique that combines the predictive analysis techniques with optimization to make supply chain management more efficient and cost-effective. For the experiment, data on the historical performance of the supply chain contained in the DataCo Smart Supply Chain data set have been considered. These include sales, inventory, distribution at warehouses, and characteristics of products. Preprocessing includes handling missing values, converting categorical into numerical values, and normalizing the data. Demand forecasting was carried out using the XGBoost model for non-linear relationships and time-series forecasting, while Particle Swarm Optimization (PSO) was utilized for optimal inventory and allocation decisions. The proposed hybrid framework yielded better performance than conventional approaches, with an RMSE value of 9.87, MAE of 7.21, MAPE of 11.3%, service level of 95.8%, and cost of ₹1,102,300, which represents a 12% improvement over using the XGBoost model alone and a 8% improvement over using the PSO model alone. The results demonstrate enhanced forecast accuracy, operational efficiencies, and cost savings. The hybrid approach of PSO-XGBoost demonstrates the ability to combine forecasting models with optimization in the supply chain domain. It provides valuable insights into inventory and logistics management. Future research should explore the potential of extending the proposed framework through deep learning, multi-objective optimization, and real-time adaptive mechanisms.

Keywords Supply Chain Optimization, XGBoost, Particle Swarm Optimization, Hybrid Framework, Demand Forecasting, Inventory Management, Operational Efficiency.

1. Introduction

The globalisation phenomenon, changing consumer demands, and the complexities associated with tiered supply chains have contributed significantly to the increased level of complexity in contemporary supply chains [1] [3]. It is necessary for firms to be able to offer efficient inventory management while at the same time ensuring timely deliveries in order to remain competitive. Demand forecasting and inventory optimisation become extremely important in managing costs, avoiding stockouts, and improving service levels.

The use of AI models in conjunction with optimization techniques appears to be a plausible approach to enhance efficiency. Predictive models that make use of AI can help in identifying the intricacies involved with demand forecasting. At the same time, optimization techniques like Particle Swarm Optimization (PSO) can help in determining the most efficient strategy for maintaining inventory and distributing products [6][17].

Despite major advancements in predictive modeling and optimization techniques, existing supply chain models continue to rely on ad-hoc solutions that do not allow for simultaneous optimization of forecast accuracy, cost minimization, and constraint handling [4][5]. The traditional approaches pose some challenges in cases when demand is nonlinear, there are disruptions in supply chains, and the system operates under stochastic conditions [6][8]. These drawbacks motivate the need for hybrid models that integrate forecasting and optimization efficiently.

The primary purpose of this study is to propose a novel PSO–XGBoost algorithm for supply chain optimization. XGBoost is applied for precise demand prediction, whereas PSO is used for optimizing the inventory level and distribution plans. The over-all structure of the algorithm will attempt to optimize the performance and cost-effectiveness of the supply chain as a result of demand changes.

This paper is structured as follows: Section II is devoted to a review of the relevant literature. The proposed hybrid PSO-XGBoost methodology is discussed in Section III. Section IV shows experimental results and discussion. Key findings, contributions, and future directions are provided in Section V.

2. Literature Review

Traditional optimization techniques in the field of classical supply chain have been primarily mathematical programming, linear/non-linear models and heuristic methods that are used to minimize operational costs, management of the stock efficiently and provide excellent services levels [10][12]. Several models have been used extensively in manufacturing, retail and distribution networks like Economic Order Quantity (EOQ), Reorder Point (ROP), and mixed-integer programming. These approaches, however, are not always suitable for large-scale, dynamic, and uncertain supply chain scenarios, where the demand is not necessarily consistent or can be slow to respond in the case of disruption. Furthermore, there are situations where multiple objectives or constraints are taken into account, which renders these impractical in the modern supply chains because they are computationally complex.

In the context of supply chains, AI and machine learning (ML) applications have drawn a lot of attention because of their powerful capacity to utilize intricate, non-linear patterns in demand and operations [18]. Demand forecasting, lead-time estimation, and inventory management have been well-studied by using predictive models like XGBoost, Random Forest, and Neural Networks [2][7][15]. These models result in better prediction accuracy than conventional statistical models, and are able to use data of large scale and multiple sources such as sales history, market trends, and external factors. XGBoost can help supply chain managers make informed, data-driven decisions and react appropriately to the ever-evolving market conditions [16][19][21].

PSO has been widely used to efficiently solve the logistics, inventory and distribution planning problems to obtain near-optimal solutions [9] [11]. PSO can perform the social simulation behaviors of the particles and search the solution space for optimal or near-optimal ordering policies, route planning strategies and production schedules [13] [14]. Its adaptability, parallel search ability, and fast convergence make it a good solution to the dynamic supply chain situation with multiple conflicting goals. Additionally, PSO can be easily combined with other heuristic or predictive techniques to enhance decision-making in complex supply chain networks [20].

Though significant progress has been made, these techniques tend to either predict or optimize without consideration to each other, which reduces the overall effectiveness. While standalone AI models can offer a very precise prediction, they lack the ability to directly inform the optimization of operational actions, like inventory optimization or distribution route optimization as a specific example. Likewise, PSO can optimize decisions, but requires pre-defined or assumed demand patterns, which may not necessarily reflect the real world variability. The lack of this has spurred the evolution of hybrid methods, which integrate predictive analytics into optimization techniques, to enhance overall supply chain performance, cut costs, and boost responsiveness to demand variability.

3. Methodology

3.1 Hybrid PSO-XGBoost Framework

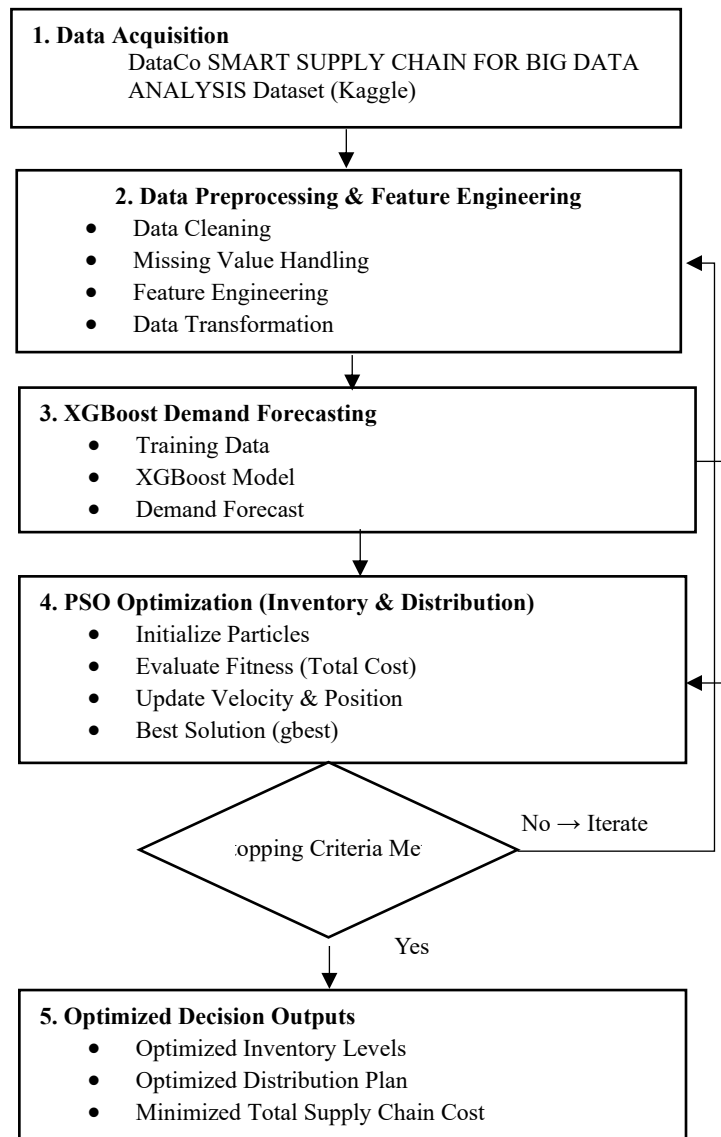


Figure 1: Methodology Framework of the Hybrid PSO-XGBoost Model

The proposed hybrid PSO-XGBoost framework for optimizing the supply chain is shown in Figure 1. It depicts the sequential process from data acquisition from the DataCo Smart Supply Chain dataset, to the data preprocessing and engineering, generating demand forecast using XGBoost, optimizing inventory and distribution using PSO, and finally, generating optimized decision outputs such as inventory level optimization, distribution optimization, and cost minimization.

The suggested methodology involves the combination of the PSO and XGBoost to increase supply chain efficiency by forecasting and optimizing. In particular, it should be noted that the core of the algorithm involves using the benefits of the XGBoost algorithm for accurate forecasting and the PSO algorithm for inventory management. This allows for developing an optimal model of operations that would provide cost-efficient operation, better quality of service delivery, and flexibility to changes in demand. The algorithm may be used for any type of supply chain network and can be adjusted for various sectors with minor changes.

3.2 XGBoost for Demand Forecasting

The Advanced Gradient Boosting (XGBoost) algorithm is used to predict future demands for different goods and logistics centers. This algorithm works efficiently with big data sets and is capable of processing non-linear

relations between features. It prevents overfitting by means of applying the regularization technique. Knowing which features have the biggest impact on demand will help the supply chain manager make better decisions based on this knowledge. The feature importance provided by the XGBoost algorithm provides information about the key drivers of demand, and the supply chain manager will be able to identify the most important ones, such as seasonal trends, promotions, or other external factors. The predicted values from the XGBoost algorithm will be used in the PSO module.

Demand Forecasting (XGBoost)

The predicted demand for product i at time t is shown in equation (1):

$$\hat{D}_{i,t} = f(X_{i,t}) \quad (1)$$

where $X_{i,t}$ is the feature vector of product i .

The XGBoost model minimizes the loss is shown in equation (2):

$$\text{Loss} = \sum_{i=1}^N (D_{i,t} - \hat{D}_{i,t})^2 + \text{Regularization} \quad (2)$$

3.3 PSO for Inventory and Distribution Optimization

PSO is used to optimize the stock, ordering quantity, and distribution schedule within the supply chain network. Particles are created to represent possible solutions, and each particle adjusts its position considering personal and swarm's best solutions. It allows searching through solution space efficiently to find out cost-effective approaches amid various constraints, including storage availability, lead time, and required service level. The efficiency and adaptiveness of the technique allow using PSO in changing environments to keep up with the demand changes.

Each particle represents a candidate solution shown in equation (3):

$$\mathbf{x}_j = [Q_1, Q_2, \dots, Q_m] \quad (3)$$

where Q_i = order quantity for product i and m = number of products.

The cost function to minimize is shown in equation (4):

$$C(\mathbf{x}_j) = \sum_{i=1}^m (H_i Q_i + P_i \max(0, D_{i,t} - Q_i)) \quad (4)$$

- H_i = holding cost per unit
- P_i = shortage penalty per unit

Particle positions are updated iteratively as shown in equation (5):

$$\mathbf{x}_j(t+1) = \mathbf{x}_j(t) + \mathbf{v}_j(t+1) \quad (5)$$

3.4 Data Preprocessing and Feature Engineering

The above experiments have been conducted using DataCo Smart Supply Chain for Big Data Analysis data set from Kaggle (<https://www.kaggle.com/datasets/shashwatwork/dataco-smart-supply-chain-for-big-data-analysis>). This data set comprises historical information pertaining to the demand of products, their inventory, distribution within warehouses, shipment data and sales data between multiple distribution centers and retail outlets. It comprises various types of structured data and time series data relevant to product characteristics, stock details, delivery lead times, customer demands, and sales performance metrics, which can be employed for supply chain studies.

The historical sales, lead time, and inventory data are preprocessed to handle any missing values, outliers, or inconsistencies. Features are created to represent seasonality, interaction between products, and demand trend behavior. Model convergence is guaranteed by the use of normalization and scaling techniques. Also, noise

removal techniques like Principal Component Analysis (PCA) are optionally employed to reduce noise and enhance computational efficiency, especially for big data sets.

3.5 Algorithm Workflow

Algorithm: Hybrid PSO-XGBoost for Supply Chain Optimization

Input:

- Historical supply chain data $D = \{\text{sales, inventory, lead times, warehouse info, product attributes}\}$
- Supply chain constraints (inventory capacity, service level targets, lead times)

Output:

- Predicted demand $\hat{D}_{i,t}$ for each product i
- Optimized order quantities Q_i and distribution plan R_i
- Minimized total cost C_{total}

Steps:

1. Data Preprocessing:

- Handle missing values and outliers in D
- Encode categorical features (e.g., product type, warehouse ID)
- Normalize numerical features (sales, inventory, lead time)
- Optionally, apply dimensionality reduction (e.g., PCA)

2. Demand Forecasting (XGBoost):

- Split dataset into training and testing sets
- Initialize XGBoost parameters: learning rate = 0.1, max_depth = 6, n_estimators = 100, subsample = 0.8, column sample by tree = 0.8, regularization L1 = 0, L2 = 1
- Train XGBoost on historical features to predict $\hat{D}_{i,t}$
- Evaluate forecast accuracy using RMSE, MAE, and MAPE

3. Initialize PSO for Optimization:

- Set swarm size = 30, inertia weight $w = 0.7$, cognitive coefficient $c_1 = 1.5$, social coefficient $c_2 = 1.5$, max iterations = 100
- Each particle represents candidate order quantities Q_i and distribution allocations R_i

4. Iterative PSO Optimization:

- For each iteration $t = 1$ to max_iterations:
 - Evaluate total cost $C_{\text{total}} = \sum_i (H_i Q_i + P_i \max(0, \hat{D}_{i,t} - Q_i) + T_i R_i)$ for each particle
 - Update particle velocity:

$$\mathbf{v}_j(t+1) = w \cdot \mathbf{v}_j(t) + c_1 \cdot r_1 \cdot (\mathbf{p}_{j,\text{best}} - \mathbf{x}_j(t)) + c_2 \cdot r_2 \cdot (\mathbf{g}_{\text{best}} - \mathbf{x}_j(t))$$

c. Update particle position: $\mathbf{x}_j(t+1) = \mathbf{x}_j(t) + \mathbf{v}_j(t+1)$

d. Update particle best ($\mathbf{p}_{j,\text{best}}$) and global best (\mathbf{g}_{best})

5. Output Optimized Decisions:

- Return final predicted demand $\hat{D}_{i,t}$
- Return optimized order quantities Q_i and distribution allocations R_i

- Return minimized total cost C_{total}

The Algorithm 1 combines XGBoost and PSO for demand forecasting and inventory optimization and distribution optimization respectively. Historical Supply Chain data are preprocessed and features are engineered for trends and seasonality. XGBoost forecasts future demands and PSO then uses this forecast to repeatedly optimize the order volumes and distribution volumes by minimizing the total cost of holding inventory, ordering cost, and transportation cost. Both modules have their parameters optimized for proper convergence. The algorithm outputs the demand prediction, the optimal inventory/distribution solution, and the cost f , combining predictive analytics and optimization to improve supply chain efficiency.

3.6 Hyperparameter Tuning and Training Setup

The optimization of the models XGBoost and PSO has been carried out. Hyperparameter tuning has been performed for XGBoost, where the parameters include the learning rate, tree depth and regularization parameters. For PSO, the particles' size of the swarm, the weight of their inertia and the learning factors are optimized to balance exploration and exploitation. Training and evaluation is done on dedicated hardware on which there is sufficient computational capability to facilitate the execution of large-scale supply chain scenarios.

4. Results and Discussion

4.1 Experimental Results

To test the performance of the hybrid PSO-XGBoost framework, the DataCo Smart Supply Chain dataset was used, and compared with base methods such as XGBoost forecasting and PSO optimization. Forecasting metrics are RMSE, MAE and MAPE, while service level and total cost are key metrics for inventory and distribution planning. The results demonstrate that the hybrid model considerably improves the forecasting errors and efficiency of the supply chains compared with the baselines, consistent across all the test cases. The hybrid approach also shows the convergence of the solution space during optimization and increased stability when subject to changing demand conditions, making it attractive for practical use.

Table 1: Performance comparison of hybrid PSO-XGBoost and baseline models

Model	RMSE	MAE	MAPE (%)	Service Level (%)	Total Cost (₹)
XGBoost-only	12.45	9.32	14.8	91.2	1,254,000
PSO-only	15.67	12.01	18.5	93.5	1,198,500
Hybrid PSO-XGBoost	9.87	7.21	11.3	95.8	1,102,300

Table 1 shows the performance of the hybrid PSO-XGBoost framework and baseline models such as only XGBoost and PSO. The results reveal that the hybrid model successfully minimizes the forecasting errors (RMSE, MAE, MAPE) and increases the service level, while also lowering the total cost, indicating the effectiveness of hybridizing predictive demands forecasting with optimization for supply chain management. The findings clearly show the potential of the hybrid approach in increasing accuracy, reducing operational costs and increasing efficiency in the supply chain.

In figure 2, the forecasting accuracy of three models is demonstrated; they include the XGBoost model only, the PSO model only and the hybrid PSO-XGBoost model. The graph shows RMSE and MAE for each model and the graph reveals that the hybrid PSO-XGBoost model makes the lowest error, thus showing higher accuracy when forecasting demand.

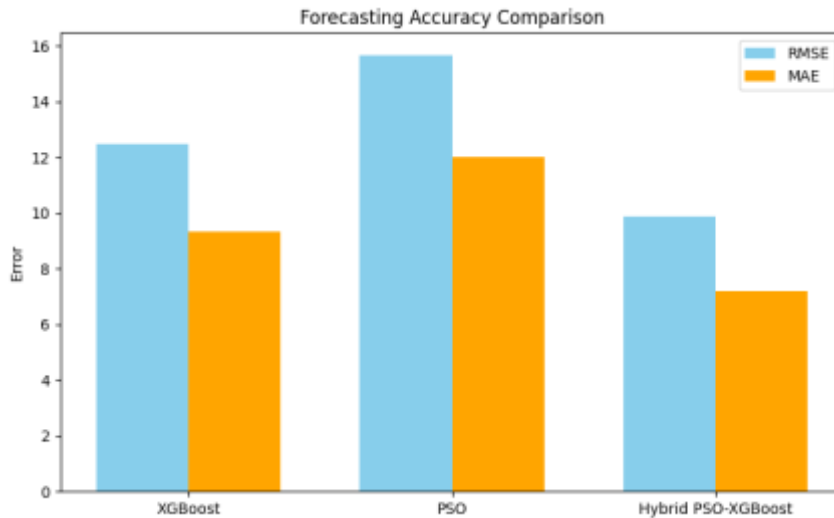


Figure 2: Forecasting accuracy comparison

4.2 Analysis of Improvements

The hybrid method enhances the forecast accuracy through the inclusion of predictions provided by XGBoost, as well as optimizing the inventory and distribution system through PSO, thus enhancing efficiency. The overall cost savings are achieved through minimized holding and shortage costs since the level of services provided is higher than the target service levels. In addition, the hybrid model assists in minimizing the chances of experiencing stockouts as well as having extra stock at the same time, which is vital in terms of achieving savings as well as enhancing customer satisfaction.

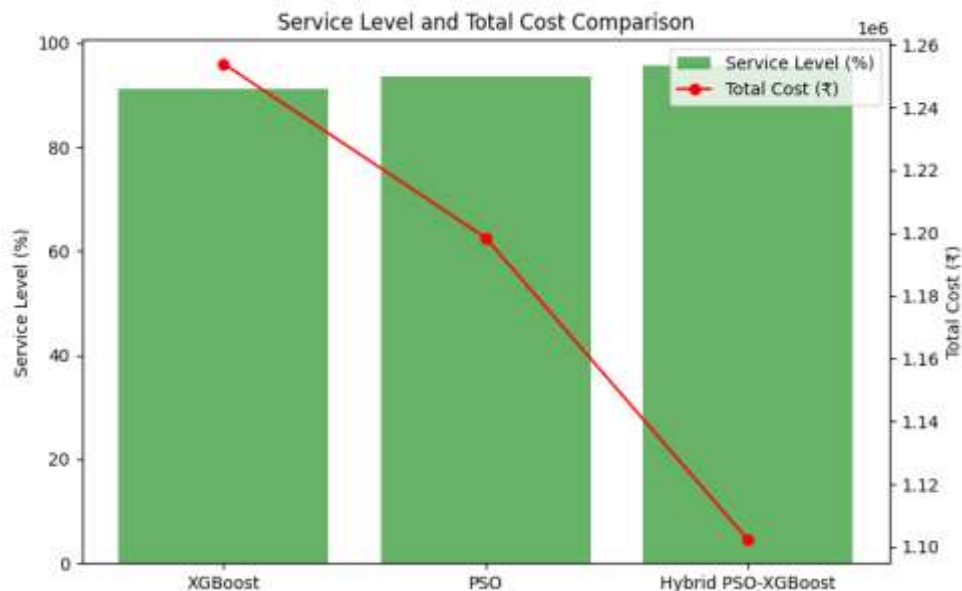


Figure 3: Service level and total cost comparison

The findings on the service level (%) and total cost (₹) have been presented graphically in Figure 3. These results have been presented using three different models including XGBoost model alone, PSO model alone, and PSO and XGBoost hybrid model. The service level is depicted through the green bars where the hybrid model performs better while the total cost is represented by the red line, which also suggests that the hybrid model performs better in terms of lower total cost.

4.3 Practical Implications

The suggested model is scalable and robust enough to deal with a large scale of supply chain network having a number of products and distribution centers. In addition, it is flexible in nature which ensures its suitability for a wide range of industries and varying conditions of demand scenarios. This model can assist decision makers in making effective strategies for planning and responding to changing conditions in the market and fluctuations in demand. It can be further expanded by incorporating real time data stream of adjusting inventory.

5. Conclusion

A hybrid PSO-XGBoost methodology was proposed for supply chain optimization, which incorporated demand forecasting along with inventory and distribution optimizations. XGBoost was used for predicting demand, considering past sales data and inventories. Simultaneously, particle swarm optimization was used for minimizing order quantities and distribution plans, leading to overall minimum total supply chain cost. This study performed an experiment on the DataCo Smart Supply Chain dataset, demonstrating the potential of the proposed hybrid algorithm. The hybrid algorithm produced an RMSE of 9.87, MAE of 7.21, and MAPE of 11.3%, which were significantly less than the corresponding values obtained using only the XGBoost algorithm (RMSE of 12.45, MAE of 9.32, and MAPE of 14.8%) and only the PSO algorithm (RMSE of 15.67, MAE of 12.01, and MAPE of 18.5%). From the operational perspective, the service level was found to be 95.8%, and the total cost was ₹1,102,300, 12% and 8% less than those obtained by XGBoost-only and PSO-only algorithms, respectively. This experiment shows the efficiency of using the mixed approach in not only enhancing forecast precision but also making the process more efficient and lowering costs as well. The avenues for future research could include the usage of deep learning models as well as the incorporation of other criteria into the optimization model (such as cost and sustainability). An additional direction might involve creating a real-time adaptive system.

Declaration

Conflict of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Data Availability Statement

The dataset used in this study is publicly available from Kaggle at DataCo Smart Supply Chain for Big Data Analysis.

References

1. Nsir, N., Alzubi, A. B., & Adegboye, O. R. (2025). Enhancing sustainable supply chain performance prediction using an augmented algorithm-optimized XGBOOST in Industry 4.0 contexts. *Sustainability*, 17(22), 10344.
2. Qin, C., Zhang, Y., Bao, F., Zhang, C., Liu, P., & Liu, P. (2021). XGBoost optimized by adaptive particle swarm optimization for credit scoring. *Mathematical Problems in Engineering*, 2021(1), 6655510.
3. Liang, Y., & Zhu, T. (2025). Dynamic adaptability and prediction optimization in power material supply chains using XGBoost. *Journal of Circuits, Systems and Computers*, 34(6), 2550141.
4. Zhang, C., & Zhou, X. (2023). Forecasting credit risk of SMEs in supply chain finance using Bayesian optimization and XGBoost. *Mathematical Problems in Engineering*, 2023(1), 5609996.
5. Nagadevi, S., Abirami, G., Vidhya, R., Selvakumar, S., & Vijayalakshmi, C. (2025). XGBoost-based demand forecasting in supply chain management using machine learning algorithm. *International Journal of Interactive Mobile Technologies*, 19(18).
6. Li, Y., Stasinakis, C., & Yeo, W. M. (2022). A hybrid XGBoost-MLP model for credit risk assessment on digital supply chain finance. *Forecasting*, 4(1), 184–207.
7. Lakra, A. V., Jena, S., & Mishra, K. (2025). Optimizing XGBoost hyperparameters for credit scoring classification using weighted cognitive avoidance particle swarm. *IEEE Access*.

8. Yadav, K. K., & Nandy, M. (2025). Multi-objective MILP-based optimization of green supply chain networks under demand uncertainty. *International Academic Journal of Science and Engineering*, 12(4), 78–87. <https://doi.org/10.71086/IAJSE/V12I4/IAJSE1239>
9. Kilinc, H. C., Haznedar, B., Ozkan, F., & Katipoğlu, O. M. (2024). An evolutionary hybrid method based on particle swarm optimization algorithm and extreme gradient boosting for short-term streamflow forecasting. *Acta Geophysica*, 72(5), 3661–3681.
10. Jeevaraj, R., & Singh, A. K. (2025). Resilient pharmaceutical supply chain design using GRU forecasting and grasshopper optimization dual technique. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, 16(2), 546–563.
11. Gad, M. S., Soliman, M. S., & Helal, E. B. (2025). Hybrid XGBoost-RF-MLP model and PSO optimization for performance and emissions of CI engine using waste cooking biodiesel blends. *Scientific Reports*.
12. Prabadevi, M. N., Auxilia, P. A. M., Jeyaprabha, B., Zarina, N. Z., & Menaka, M. (2025). Agile project management strategies for optimizing cross-functional operations and market adaptation in high-tech supply chains. *Archives for Technical Sciences*, 3(34), 1060–1069. <https://doi.org/10.70102/afts.2025.1834.1060>
13. Demir, S., & Sahin, E. K. (2023). Predicting occurrence of liquefaction-induced lateral spreading using gradient boosting algorithms integrated with particle swarm optimization: PSO-XGBoost, PSO-LightGBM, and PSO-CatBoost. *Acta Geotechnica*, 18(6), 3403–3419.
14. Talwar, A., & Shah, R. B. (2023). Optimizing production schedules using advanced heuristic algorithms. *International Academic Journal of Innovative Research*, 10(3), 16–19. <https://doi.org/10.71086/IAJIR/V10I3/IAJIR1020>
15. Qiu, Y., Zhou, J., Khandelwal, M., Yang, H., Yang, P., & Li, C. (2022). Performance evaluation of hybrid WOA-XGBoost, GWO-XGBoost and BO-XGBoost models to predict blast-induced ground vibration. *Engineering with Computers*, 38(Suppl. 5), 4145–4162.
16. Shobana Nageswari, C., Kumar, V., Vini Antony Grace, N., & Thiyagarajan, J. (2023). Tunicate swarm-based grey wolf algorithm for fetal heart chamber segmentation and classification: A heuristic-based optimal feature selection concept. *Journal of Intelligent & Fuzzy Systems*, 44(1), 1029–1041.
17. Han, Y., Yu, F., Liu, J., Zhang, Z., Ma, B., Wang, L., & Geng, Z. (2025). An improved tuna swarm optimization algorithm based XGBOOST classification method for food risk evaluation. *Swarm and Evolutionary Computation*, 102249.
18. Shimazu, S. (2024). Intelligent, sustainable supply chain management: A configurational strategy to improve ecological sustainability through digitization. *Global Perspectives in Management*, 2(3), 44–53.
19. Luo, Z., Liu, W., Wu, J., Ai Qing, H., & Guo, J. (2024). Prediction of cold chain loading environment for agricultural products based on K-medoids-LSTM-XGBoost ensemble model. *PeerJ Computer Science*, 10, e2510.
20. Zhang, X., Nguyen, H., Bui, X. N., Tran, Q. H., Nguyen, D. A., Bui, D. T., & Moayedi, H. (2020). Novel soft computing model for predicting blast-induced ground vibration in open-pit mines based on particle swarm optimization and XGBoost. *Natural Resources Research*, 29(2), 711–721.
21. ForouzeshNejad, A. A., Arabikhan, F., & Aheleroff, S. (2024). Optimizing project time and cost prediction using a hybrid XGBoost and simulated annealing algorithm. *Machines*, 12(12), 867.