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ECONOMIC MODELING AND SIMULATION IN THE INDUSTRIAL SUPPLY CHAIN MODEL USING PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract. *The economic developments revolve around the distributed and connected supply chains across different industries forming a circular model. The circular model depends on productivity, distribution, and revenue for better standardization. Still, optimizing the industrial economy depending on supply chains is required to reduce overhead costs. Thus, the main contribution of this work is to suppress the cost overheads in unplanned supply chain distributions. In addition, revenue and industrial productivity are enhanced with the help of the particle swarm optimization (PSO)-induced connecting model (CM). The proposed connecting model identifies the least possible circular chain design for product/productivity distribution. The design is based on PSO optimization, wherein the least cost-effective connecting position is identified for each distribution. The minimum cost-effective or less overhead-based supply chain design has been opted for because the distribution is iterative. The best-fit solution is identified using high-precision supply chain connectivity and low-cost overheads. This best-fit solution is iterated through new distribution designs with local and global positions. Therefore, standardization is instigated with the identified global solutions for supply chain economy management.*
Keywords: Economy modeling, Industrial model, PSO, Supply chain

1. **Introduction.** A supply chain is a network or system where every organization, activity, resource, and technology is used to create a certain product or sale. An industrial supply chain is to design or create a product for customers. An economic model is required for every industrial supply chain system [1]. The economic model maintains or identifies the economic behaviors of industries. Industrial supply chain management is a complicated task to perform in industries. The industrial organization's economic supply chain model is to understand the exact performance and significance of the systems [2]. Construction economic theory is used here to identify the actual economic status of an organization which produces relevant information for further processes. Economic theory provides feasible features and patterns for the behavior detection process [3]. Circular economy (CE) paradigms are also used in the industrial supply chain. An empirical analysis is implemented in CE to realize industries' sustainable information and condition [4]. Empirical analysis reduces the gap between strategies and policies, which enhances

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the performance and efficiency of industrial supply chain systems. Various operation and functions are performed in the system that improves the sustainability and feasibility of CE in organizations [5].

Economic optimization is a process that improves efficiency and reduces costs in trading organizations and industries. Certain economic optimization techniques and methods are used in supply chain (SC) management systems [6]. The economic optimization model solves various problems and issues which occur in management systems. Mixed-integer linear programming (MILP) model is used in supply chain systems. MILP identifies optimization problems and detects the actual cause of problems in SC [7]. MILP increases the overall accuracy in optimization problem detection, which enhances the performance and efficiency of supply chain management systems. A robust optimization approach is used for economic optimization in SC [8]. The economic value added (EVA) metric is applied for the optimization process. The robust optimization approach identifies the operational risk which is presented in SC management systems. Operational risks are analyzed based on empirical analysis that produces relevant information for the optimization process [9]. Symmetric fuzzy linear programming (SFLP) is used in SC to solve economic optimization problems. SELP uses the resource task network (RTN) method to validate optimization capabilities in SC management systems [10].

Optimization models are mostly used in industrial supply chain (SC) systems. An optimization model is mainly used to improve SC systems' performance, feasibility, and reliability [11]. An optimization process is a very important task to perform in SC that provides necessary information for various processes. A strategic supply chain optimization model is used for industrial SC. SC identifies parameters and patterns, which produces relevant information for further processes [12]. Features of industries provide data that reduces latency in the computation and optimization process. Industries require a proper optimization process that enhances the effective range of enterprises [13]. Optimization maximizes decision-making accuracy, reducing computation latency and error in SC systems. The strategic network optimization model is used in industrial supply chain systems [14]. The strategic optimization model identifies the problems and issues which are presented in SC and produces solutions to solve problems. Optimization problems mostly occur due to data loss and workload in SC that reduces the sustainability of the systems [15]. However, the business models are successfully analyzed in the industrial development, the business model faces the production and cost overhead issues. Therefore, the main objective of the paper is to improve the overall industrial production and minimize the cost overheads.

Then the rest of the paper is organized as follows. Section 2 discusses the various researchers' opinions regarding the business models to improve the overall industrial productivity. Section 3 discusses the working process of particle swarm optimization (PSO)-induced connecting model and excellency of the system is evaluated in Section 4. Conclusion is described in Section 5.

2. **Related Works.** Divsalar et al. [16] introduced a decision-making model to evaluate the lean, agile, resilient, and green (LARG) paradigm in the supply chain. Supply chain operations are evaluated based on certain features and conditions. Network relationships are also identified using supply chain elements and dimensions. The introduced evaluation model improves effectiveness and competitiveness among the systems. The introduced model achieves high accuracy in evaluation, enhancing the LARG performance of the systems.

Yani et al. [17] proposed an adaptive fuzzy multi-criteria model for the agroindustry supply chain. The main aim of the proposed model is to improve the sustainability assessments of supply chain systems. A fuzzy inference system (FIS) is implemented here to assess sustainability, reducing errors in the evaluation process. FIS improves the sustainability performance range of the agroindustry. Compared with other models, the proposed model increases industries' overall quality and recovery.

Xie et al. [18] designed a government subsidy analysis-based game model for green financial supply chain systems. Retailers' manufacturers, and customer details are identified based on the government's conditions. The proposed model is mostly used in rural areas, which require proper policies and schemes to improve the development and accuracy of small enterprises. Rural revitalization strategies are used here to identify product and manufacturer relationships. The proposed model maximizes the efficiency and reliability level in developing enterprises.

Zhang and Lam [19] developed a value-based management approach to evaluate the impact of e-collaboration on supply chain systems. Economic value added (EVA) is implemented here as value-based performance metrics. EVA provides the exact unified metrics which are available in supply chain systems. The management approach provides value which is amplified in supply chain systems by e-collaboration. The analyzed study produces the actual effects and impacts of e-collaboration in information-sharing systems.

Mohammed et al. [20] introduced the mixed-integer linear programming (MILP) model closed-loop supply chain (CLSC). The main aim of MILP is to mitigate carbon emissions in CLSC. MILP collects the necessary information which is required for evaluation and detection processes. Experimental results show that the MILP model reduces supply chain networks' overall carbon emission ratio. The introduced model maximizes supply chain networks' robustness, quality, and performance levels.

Köhler et al. [21] discussed the distributed model predictive control for supply chain management systems. Customer forecast information is used here that provides appropriate information for prediction control. Predictive information is required for the sharing process, which is a complicated task in management systems. The distributed model analyzes operations and functions of the supply chain, which reduces computation latency. The discussed model achieves high accuracy in the prediction, which enhances the efficiency and feasibility of supply chain management.

Centobelli et al. [22] proposed a new evaluation model for small and medium enterprises (SMEs). The main aim of the proposed model is to explore the relationship among green economics, social pressure, circular economy, and environmental commitments of SMEs. The identified relationship information produces feasible data for the evaluation process, enhancing SMEs' performance. The proposed model improves the sustainability and efficiency range of SMEs. The proposed model also maximizes the circular economy capabilities of SMEs.

Qian et al. [23] introduced a scenario-based economic model predictive control (EMPC) framework. EMPC is mostly used for integrated inventory and transportation management in supply chain systems. Demands and scenarios are analyzed based on conditions that provide necessary data for further processes. EMPC produces real-time operations to the supply chain that reduces cost and energy consumption ratio. When compared with other frameworks, the proposed EMPC framework improves the effectiveness and performance of supply chain systems.

Ahmad et al. [24] designed a multi-objective model for pharmaceutical supply chain systems. The main goal of the designed model is to optimize the socio-economic performance of the systems. Various optimization problems occur during optimization that is solved by providing proper solutions. Ideal solutions are provided to solve certain problems, improving the systems' energy efficiency. The proposed model increases pharmaceutical supply chain systems' overall performance and efficiency.

Ma et al. [25] proposed an integrated model using time-based competition for supply chain networks. The main aim of the proposed model is to provide time series for product productions. Time firms are provided to heterogenous customers and manufacturers to build certain products. The integrated model reduces time consumption and error ratio in the computation process. The proposed model maximizes the profits and quality of products that enhance the performance of supply chain networks.

Salçuk et al. [26] introduced a multi-objective optimization model using a goal programming technique for a closed-loop supply chain (CLSC). Decision variables and parameters are identified by programming techniques that reduce latency in identification. Parameters contain details such as a product's demand, cost, production, capacity, and carbon emission range. The proposed model reduces the computation process's cost and energy consumption levels. The introduced model improves the production rate, performance, and sustainability range of CLSC.

Garai and Roy [27] designed a customer-centric closed-loop supply chain management model. The designed model detects the classical and traditional performance by customer satisfaction. Customer-satisfaction index and parameters provide optimal information that is required to perform a certain task in supply chain systems. Optimization problems and errors are also reduced by understanding T-sets which are produced by management systems. The proposed model improves the cost-effectiveness and satisfactory range of customers in the T environment.

Li et al. [28] introduced a fuzzy integrated optimization model for logistics supply chain systems. The demand of uncertainty background is verified based on certain parameters that provide feasible data for the optimization process. The impact of uncertainty is reduced by logistics services. The introduced model reduces the time and energy consumption range in performing tasks, improving the systems' performance. Experimental results show that the proposed model improves the effectiveness and feasibility of supply chain systems.

Ghahremani-Nahr and Ghaderi [29] proposed a robust-fuzzy optimization approach for lean supply chain (LSC) networks. The main aim of the proposed approach is to identify the exact uncertainty range in LSC. A sustainable performance indicator (SPI) is used here to detect the social aspects of LSC. The meta-heuristic method is also used here to identify the Pareto front of LSC. The proposed approach reduces the identification process's latency, which improves computation accuracy. The proposed approach enhances the efficiency and reliability of LSC networks.

3. **Proposed Particle Swarm Optimization (PSO)-Induced Connecting Model.** The economic modeling and simulation in the industrial supply chain of any country are optimized to reduce the cost overhead and make a decision for better standardization of the industrial economy based on the circular model for managing different industries. Every country has some strategy to develop and improve the distributed and connected supply chain across several industries. It is forming like a circular model for economic development and maintains the sustainability of the supply chain distribution through the circular model. The circular model relies on that country's productivity, distribution, and revenue for economic development and better standardization. Any country's economic and industrial development is improved by low-cost overhead and high connectivity between the people's demands and the supply chain. This model focuses on this demand for identifying which causes the overhead cost in the industrial supply chain through PSO and CM for suppressing the cost overheads in unplanned supply chain distribution. This

economic modeling changes the existing devices and technologies with advanced devices and creative ideas to improve economic growth by reducing the low-cost overhead. The information observed from the particular industry based on that demand/data supply chain will be processed, and the standard supply chain leads to high economic development; if the economy improves, the industrial supply chain also increases. However, the industrial supply chain is to enhance sustainable performance based on the automation of processes. Figure 1 illustrates the proposed model in an SCM process.

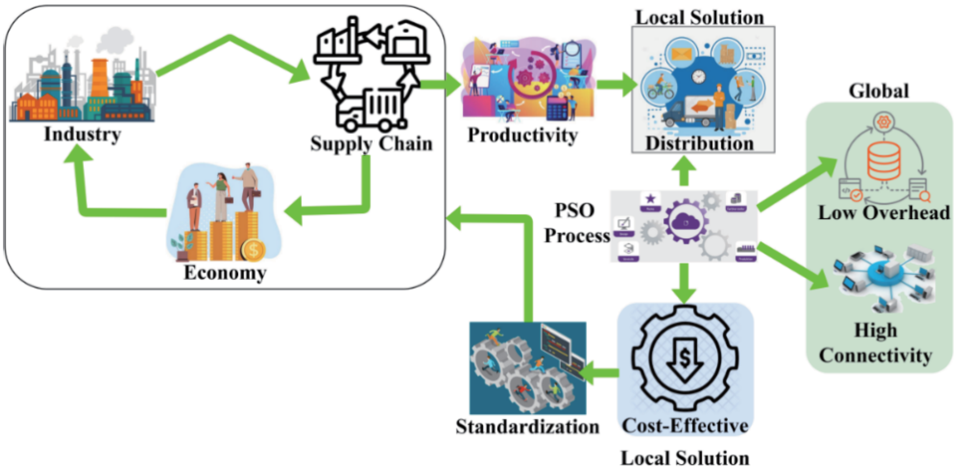

Figure 1. PSO-CM in SCM process

The PSO-induced CM is used for addressing the failures in supply chain distribution and cost overhead for improving economic developments. Therefore, the low-cost overhead can be reduced through precise supply chain distribution; it requires coordination among the economic modeling and simulation. A circular model can be employed to improve productivity while reducing overhead costs and increasing responsible supply chain production, consumption and distribution as expounded the sustainability of products available in the supply chain.

3.1. **PSO algorithm.** PSO algorithm first generates a random population based on the industrial supply chain model. Each particle that has its position, objective function, and fitness value is computed. Based on the industrial supply chain model, the PSO algorithm has no cross-mutation. Instead, the personal optimum for each particle is analyzed, and the overall optimum in the country's population, whereas the neighborhood optimum identified by the neighbors of each particle is stored to update the fitness and position value at each circular chain. This process is continuously iterated until the maximum distribution or cost-effectiveness is achieved. Every single particle goes to its local best-fit solution and final solution of the industrial economic development in each circular model. The supply chain for people depending on the economy management is expressed as

$$P_{ij}(T+1) = R^1(p_{ij}(T) - SD_{ij}(T)) + R^2(Bfs_{ij}(T) - Fs_{ij}(T)) + C \tag{1}$$

where $P_{ij}(T+1)$ represents the particle with i productivity on the jth industrial supply chain at any $T+1$ iteration. The variables $p_{ij}(T)$ and $SD_{ij}(T)$ mean population and supply chain distribution for each i and j at the circular model, R^1 and R^2 are the two random integers between $(0,1)$ and C represents a constant supply chain distribution. $Bfs_{ij}(T)$ and $Fs_{ij}(T)$ are the best-fit solution and final solution for each distribution. The new distribution of a supply chain is computed as

$$p_{ij}(T+1) = SD_{ij}(T) + P_{ij}(T+1) \tag{2}$$

Equation (2) computes the proper planned supply chain distribution output relying on productivity, distribution, and cost-effective analyzed through the PSO process with $SD_{ij}(T)$ at given time intervals. The maximum supply chain distribution of $Product_{dist} = 1$ output in high cost-effective and better standardization in that industry for identifying the least possible circular chain design. In this proposed connecting model, T means the given time intervals for analyzing industrial supply chain management. The distribution process using the best-fit solution is presented in Figure 2.

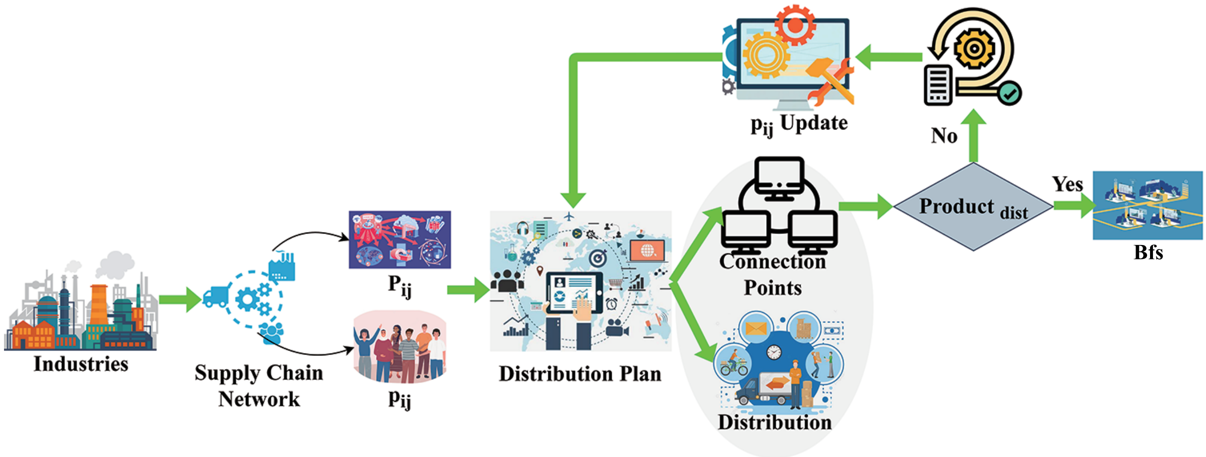

FIGURE 2. Distribution process based on best-fit solution

The best-fit solution identifies the condition $Product_{dist} = 1$ to be true for the varying $P_{ij} \in p_{ij}$. Here two concurrent processes are performed to identify the Bfs_{ij}. In the first process, $SD_{ij}(T)$ is balanced for distribution and productivity using the aforementioned condition. In the contrary case the p_{ij} is updated, for which $(T + 1)$ is required by adjusting R^1 and R^2. Therefore, the ith and jth condition balancing is sustained to prevent overhead. The augmenting ith p_{ij} is represented as the best-fit solution across multiple $(T+1)$ (Refer to Figure 2). Therefore, the product distribution and cost-effective are not constant due to the suppressing of cost overhead in unplanned supply chain distributions as $Product_{dist} \in [0, 1]$ performs in a fluctuating manner. Here, $Product_{dist} = 1$ is processed at a given time interval based on people's needs in that country, outputs in low-cost overhead. The product productivity distribution and cost-effectiveness are jointly balanced using the proposed connecting model for maximizing economic modeling and simulation.

3.2. **PSO optimization-based circular chain design.** In this proposed model for supply chain management, product distribution is minimized by unplanned supply chain distribution and cost overhead across different industries in any nation. The product distribution and cost-effectiveness are analyzed through the PSO algorithm for identifying the connecting position, and the best fitness value for each distribution is computed. The low-cost overhead occurrence is computed due to the fact that increasing population is mitigated as per Equation (1). Based on the current economy and people's demand, the cost overhead is expressed as

$$Cost_{Ovh} = \frac{(Ind_1 + Ind_2 + \cdots + Ind_n)/3 - PO^V}{F_V} \tag{3}$$

where, $Cost_{Ovh}$ is the cost overhead due to unplanned industrial supply chain distribution; this constraint $(Ind_1 + Ind_2 + \cdots + Ind_n)$ represent different industries in that country forming a circular model; PO^V means the least cost-effective position value; and F_V means the best fitness value for supply chain design.

PO^V can be expressed as

$$PO^V = \frac{PO^V_{\max} - PO^V_{\min}}{1 - C^{Ec}} \tag{4}$$

where, $PO^V_{\max}$ and $PO^V_{\min}$ are the maximum and minimum cost-effective connecting position identified in that supply chain distribution; C^{Ec} means cost-effective control in the industrial supply chain model.

F_V can be expressed as

$$F_V = \frac{P_{ij}\left(PO^V_{\max} - PO^V_{\min}\right)}{\theta(T - 2SD_{ij})C^{Ec}} \tag{5}$$

where Ind and SD are the different industries and supply chain distribution. In Figure 3, the fitness computation process is illustrated.

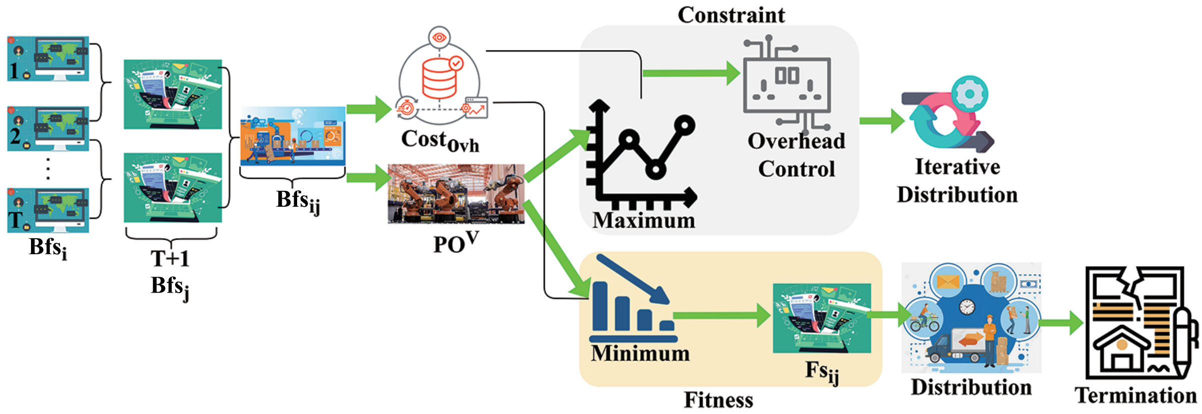

FIGURE 3. Fitness computation

The fitness is computed from the partial computation of PO^V from the recurrent $(T+1)$. For the varying T, the Bfs_i and Bfs_j are estimated using $(T + 1)$ such that Bfs_{ij} is set to identify PO^V and $Cost_{Ovh}$ is harmonized. If the $Cost_{Ovh}$ is less with PO^V (minimum), then distribution is planned. Contrarily if the other conditions occur, then iterations for redistribution are pursued (Figure 3). The iterative distribution is identified due to low-cost overhead, which can be expressed as follows:

$$P_{ij} = (\theta - 2)(T - 2SD_{ij})^2 \tag{6}$$

The unplanned supply chain distribution estimation identifies the overhead cost at the time of product distribution. The cost-effective connecting position is identified and updates the current demands of the people; it is the best-fit solution to balance industrial productivity and standardization at various time intervals. Hence, this condition $\frac{(Ind_1+Ind_2+\cdots+Ind_n)/3-PO^V}{F_V}$ exceeds in this model, then the PSO algorithm is used for better standardization. The minimum cost-effective or loss overhead-based supply chain management in any country maximizes productivity distribution and defaces the people's demands and economy across several industries. The low-overhead and high connectivity holds the best-fit solution is identified using high precision supply chain and occurrence of $Product_{dist}$ is performed through proper planning. The best-fit solution is computed to mitigate the minimum cost-effective and less costly overhead for improving the economy across multiple industries achieved through the PSO algorithm. Considering this supply chain distribution is processed based on population and demands in their country. The cost-effective position is addressed through PSO optimization for maintaining better standardization. In this proposed connecting model, the minimum cost-effectiveness is identified and analyzed for reducing overhead, and a best-fit solution varies based on the condition as in the above Equation (1). As per this model, the total population is computed to optimize the first demand supply and connected circular model for improving industries to avoid low-cost overhead at the same of supply chain management. In addition, PSO optimization is used to achieve high-precision supply chain distribution and manage better standardization of industries.

3.3. **Economy modeling using PSO.** The economy and industrial modeling are analyzed with people's demand and supply to improve the economic development as follows.
Case 1: Productivity.
Solution 1: The population-weight-based products will be manufactured and distributed to the country's people at some cost. The product distribution is performed to augment the economy modeling. The total productivity (PO^V) is manufactured randomly. The cost-effective connecting position in industrial supply chain management is expressed as

$$Q = Ind \times Product_{dist} + Ind \times T + Ind \times PO^V \tag{7}$$

Case 2: Supply chain distribution.
Solution 2: Planned supply chain distribution is computed and carried out the low-cost overhead in the supply chain model. The minimum cost-effectiveness is expressed as

$$C_{\min}^{Ec} = \frac{1}{n}\sum_{T=1}^{n}\sum_{ij}^{T}(p_{ij} - SD_{ij})^2 \tag{8}$$

Post the product distribution in the supply chain, and the circular model is served as input in the PSO optimization. Whereas T means the best-fit solution iterating time intervals output in 1 due to low-cost overhead. The minimum cost-effective-based supply chain is updated with current technologies.
Case 3: Revenue based on local and global positions for better standardization.
Solution 3: The supply chain function of every industry is required with economic development, and revenue is improved to perform a new distribution. From the minimum cost-effective identification, the distributed and connected supply chain across various industries with demands and supply is processed with high cost-effectiveness improving the economy. The revenue of the country is expressed as

$$revenue = \frac{(Ind)_{ij}}{\sum_{i=1}^{n}(p_{ij})_n} \tag{9}$$

where the revenue of the country is evaluated through low-cost overhead and high connectivity relying on local and global positions. The best-fit solution for planned supply chain distribution SC_D and product distribution $Product_{dist}$ in the jth position is computed as

$$\left.\begin{aligned} SC_D = SC_D(1-p)Product_{dist} \cdot T \\ \text{and} \\ Product_{dist} = Product_{dist}(1-p)SD \cdot T \end{aligned}\right\} \tag{10}$$

The revenue computation is performed for each distribution. The best-fit solution for the ith product distribution on the jth cost-effective connecting position $C_{position}$ is computed as

$$C_{position} = \begin{cases} SC_D + (SC_D - Product_{dist}) * F_V, & \theta \geq T \\ C_{\max}^{Ec} + (Product_{dist} - SD) * F_V, & \theta < T \end{cases} \tag{11}$$

Equation (11) computes the maximum and minimum supply chain distribution with ith industry and the jth position is connected to enhance productivity. The low-cost overhead and cost-effectiveness are identified for improving the standardization of the industry. The

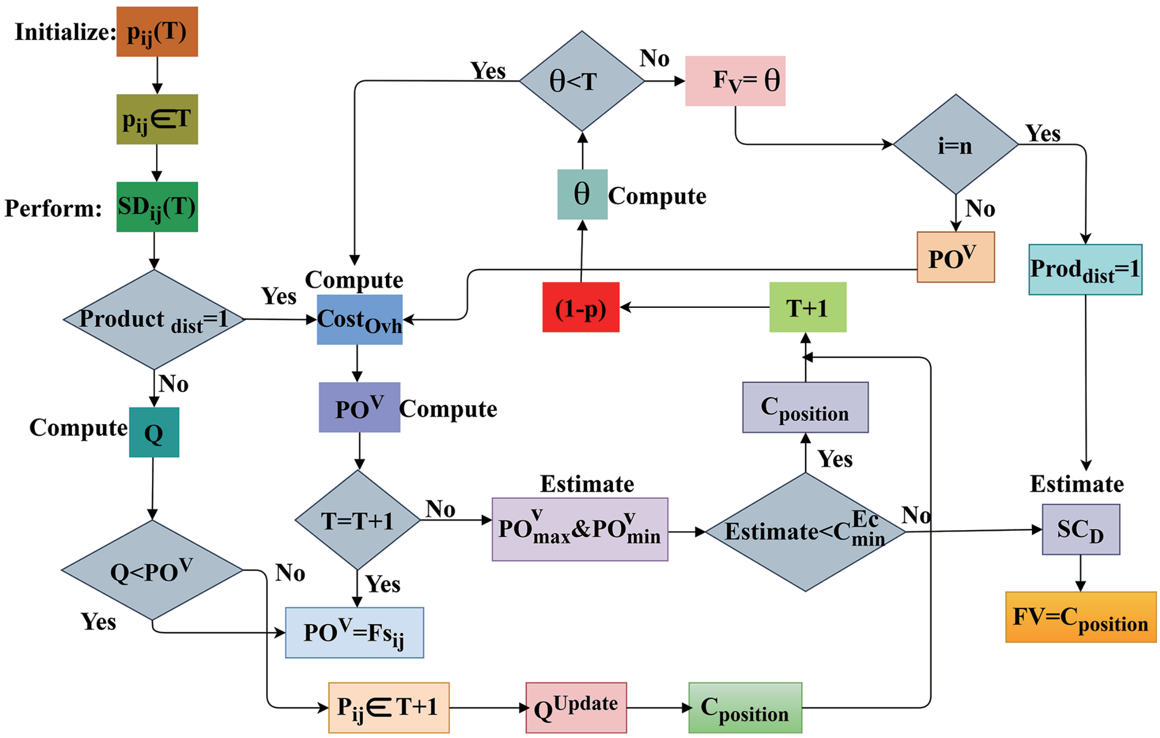

FIGURE 4. PSO process

feasible product distribution and stimulation are served as input into the PSO algorithm, sequentially distributing the products until the minimum cost-effective, or less overhead is achieved. The PSO process of the above 3 cases is illustrated in Figure 4.

The PSO process is instigated from $p_{ij}(T)$ wherein 3 conditions for 3 cases are analyzed. First, $Product_{dist} = 1$ is validated under $Q < PO^V$ that achieves a local solution Fs_{ij}. The conditional validation for $T = T + 1$ and $PO^V_{\max}$ and $PO^V_{\min} < C^{Ec}_{\min}$ is performed. Therefore, SC_D is the final solution $C_{position}$; this is achieved for $Product_{dist} = 1$ from $i = n$ condition. The alternate condition for $\theta < T$ is observed for $Cost_{Ovh}$ estimation by decreasing $(1-p)$. This decreased result is reducing cost overhead for which θ estimation is recurrent (Figure 4). The above computation for the industrial supply chain management model is used for increasing the industries for manufacturing and supplying the people's demand with balancing product distribution and cost-effectiveness using the PSO process. Therefore, the standardization of the industry is maintained with low-cost overhead and high connectivity.

4. **Discussion.**

This section presents the analysis of the proposed model using [30] data. This data extracts unit (stock), demand forecast, and distribution over various supply chain features. Considering the deviations and $C_{position}$ update post a distribution cycle, the data from 23 columns are split. This splitting relies on stocks, computed $Product_{dist} = 1$, and Q in 4, 6, and 8 columns, respectively. Figure 5 illustrates the data processing for distribution and revenue estimation.

The data extraction process relies on stock availability (production-inclusive) and distribution. This distribution is classified for $Product_{dist} = 1, 0$ (or) $0 < | < 1$. These are adverse in identifying the best solution for which $C^{EC}_{\min}$ must be a loss. Therefore, the failed and undelivered distribution due to repetition or multiple Q are estimated to be non-ideal in economic improvements (revenue) (Figure 5). From the extracted data, the analysis for failed distribution and Q requirements are presented in Figure 6.

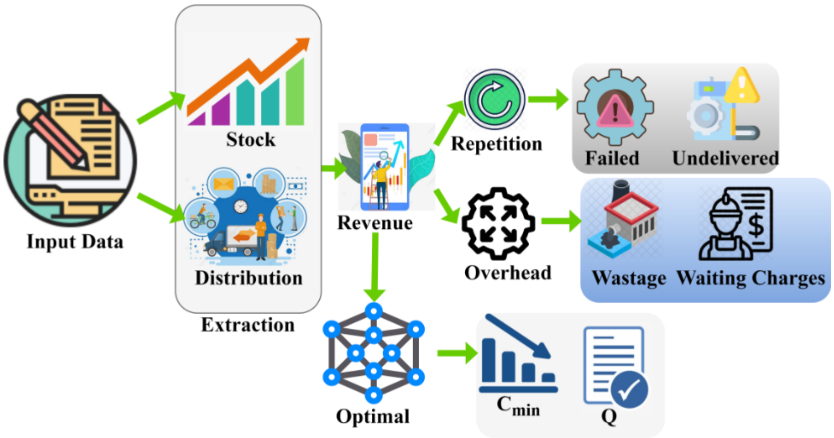

FIGURE 5. Data extraction for processing

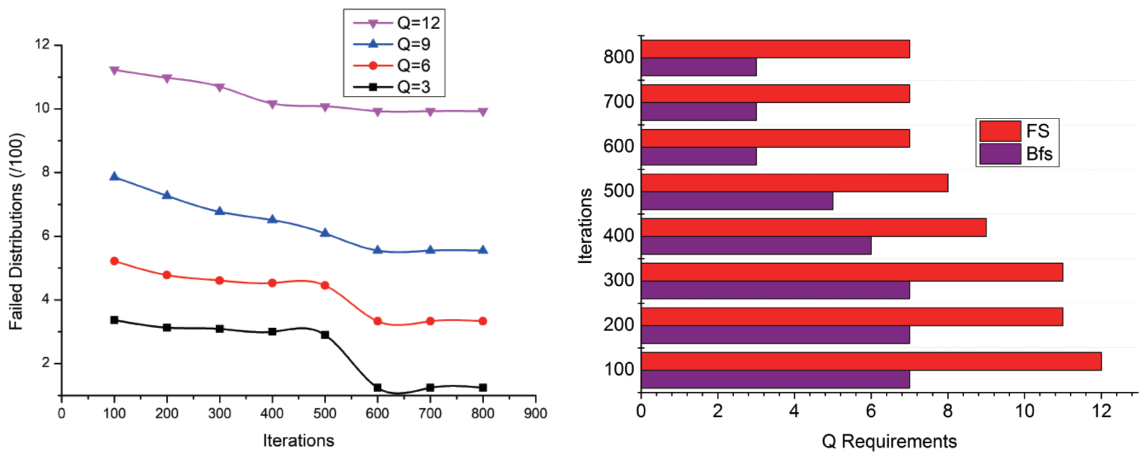

FIGURE 6. Failed distributions and Q requirements

In the varying iterations, the requirements for distribution using Bfs and Fs are identified. Considering the PO^V before Classification as $PO^V_{\max}$ and $PO^V_{\min}$, the $C_{position}$ is updated for preventing $< C^{EC}_{\min}$ condition. Therefore, Q deployments are high considering the distribution without increasing $Cost_{Ovh}$. Therefore, the PSO iterations rely on $i = n \forall PO^V$ satisfying the three cases of revenue, distribution, and production (Figure 6). Post this analysis, cost overhead for the identified Q and the improvements are analyzed with the available $C_{position}$ updates. This analysis is presented in Figure 7.

The $C_{position}$ updates are provided for reducing $< C^{Ec}_{\min}$ constraints throughout SC_D. The prime condition of $Product_{dist} = 1$ is required for maximizing distributions. If $F_V = C_{position}$, then the iteration is saturated, and no new position is required. Contrarily if a new Q is identified, then $Q < PO^V$ is attained. If this condition is true, then $Cost_{Ovh}$ is less compared to the previous $(T + 1)\forall i \in n$. Else the improvement decreases for which a new Bfs_{ij} is detected (leaving out Fs). Therefore, the optimization for $SD_{ij}(T)$ is required for $P_{ij} \in T$ provided $F_V = \theta$ is the final solution (Figure 7). From this analysis, the redistribution due to Q (required and available) is tabulated in Table 1.

The iterations are classified using $PO^V_{\max}$ and $PO^V_{\min}$ such that $Product_{dist}$ is maximized. Depending on the available F_V solutions, the required and available solutions are filtered. The filtering requires additional classification over the available $(1 - p)$. The $(1 - p)$ is augmented from the available P_{ij} (Table 1). Table 2 presents the SC_D for the varying position updates influenced by various factors.

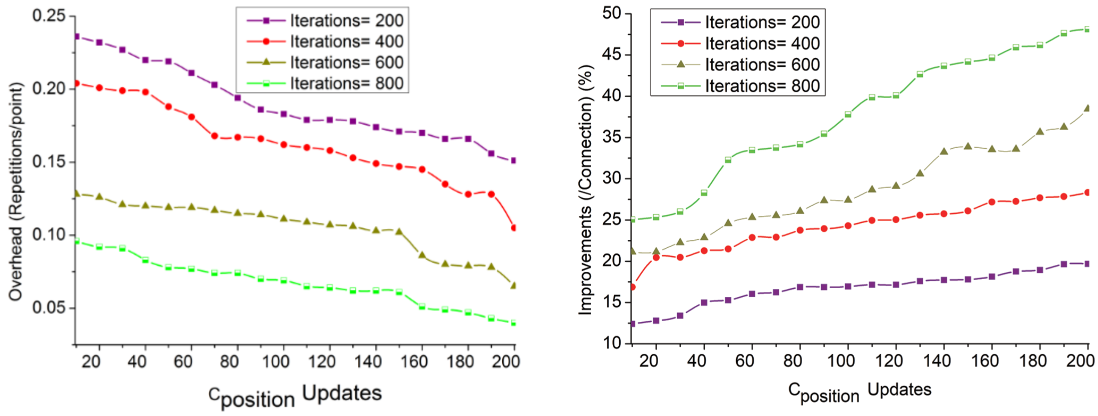

FIGURE 7. $Cost_{Ovh}$ and improvements

TABLE 1. Q (required and available) analysis

T	$PO^V_{\max}$	$PO^V_{\min}$	$Product_{dist}$	F_V solutions	Q	
					Required	Available
100	0.518	0.013	0.449	56	3	2
200	0.458	0.058	0.547	125	2	1
300	0.421	0.065	0.496	358	6	4
400	0.325	0.085	0.589	242	8	6
500	0.239	0.295	0.698	547	7	5
600	0.21	0.36	0.658	428	12	10
700	0.15	0.58	0.784	694	5	3
800	0.022	0.64	0.961	703	9	7

The distribution over the supply chain management is required for balancing R^1 and R^2 over different iterations. The F_V solutions that are higher than the local best solutions are identified for improving the supply chain distributions. This is consistent until the rescheduling, and deviating positions are varied across multiple $(T+1)$. Therefore, the changes in multiple decisive iterations are required to prevent new Q updates. Therefore, the iterated and non-iterated validations improve the distribution for maximizing $Product_{dist}$.

5. **Comparison Study.** The comparison study is performed using the metrics overhead, computing time, precision, distribution improvements, and connecting positions identified. The variants are connecting points and distributions between 1 and 12 and 5 and 75, respectively.

5.1. **Overhead.** The least possible circular chain design is identified for maximum product/productivity distribution in the country through PSO optimization under data computing time, illustrated in Figure 8. The proposed model achieves less low-cost overhead by estimating the sequential input industrial data processing depending on distributed and connected supply chain in several industries at different time intervals increasing the distribution improvements. In this PSO process, the possible product distribution is performed at any instance of $Bfs_{ij}(T)$ and $Fs_{ij}(T)$ that serves as input for supply chain management and the probability of supply chain distribution is computed. The input data from the industries are processed using Equations (3), (4), (5), (6), (7), and (8) computation. In this proposed connecting model, the overhead cost is identified using a circular

TABLE 2. SC_D for different position updates

$C_{position}$ updates	R^1	R^2	Bfs_{ij}	Fs_{ij}	Q	$Cost_{Ovh}$	SC_D
10	−0.13	0.61	4	2	12	0.237	0.58
20	−0.125	0.58	25	12	10	0.222	0.52
30	−0.011	0.55	32	24	11	0.154	0.74
40	0.015	0.54	41	36	9	0.034	0.9
50	0.152	0.61	56	45	8	0.165	0.814
60	0.121	0.45	98	81	5	0.098	0.63
70	0.214	0.41	112	96	8	0.085	0.91
80	0.258	0.32	105	83	7	0.125	0.78
90	0.247	0.458	205	159	1	0.231	0.61
100	0.198	0.265	123	96	5	0.204	0.74
110	0.214	0.501	154	122	2	0.225	0.65
120	0.258	0.601	164	135	4	0.237	0.59
130	0.365	0.421	211	159	1	0.125	0.74
140	0.415	0.217	154	132	3	0.037	0.91
150	0.387	0.388	69	41	6	0.045	0.78
160	0.341	0.542	87	63	10	0.235	0.61
170	0.408	0.415	115	78	9	0.135	0.84
180	0.365	0.478	165	112	6	0.212	0.89
190	0.398	0.26	29	20	12	0.087	0.90
200	0.422	0.47	204	155	2	0.082	0.88

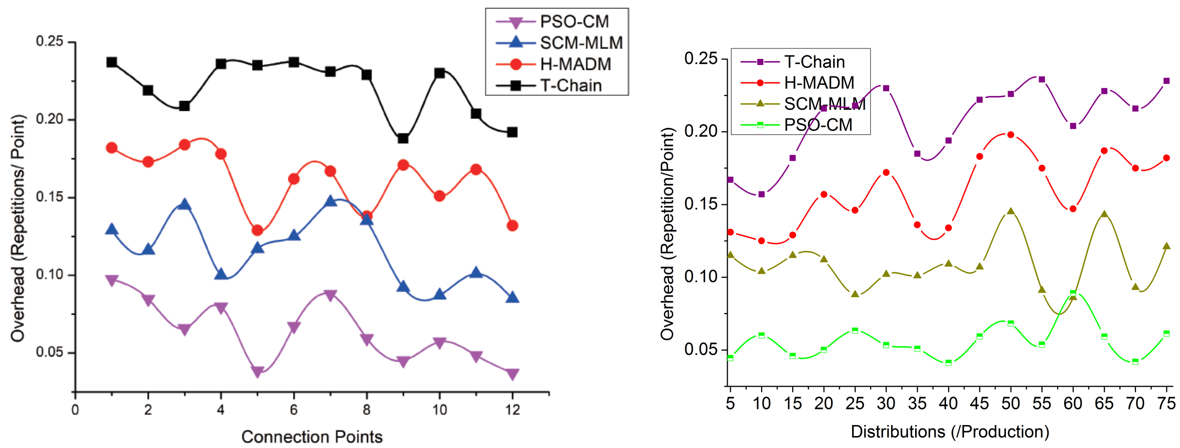

FIGURE 8. Overhead comparisons

model that relies on the least possible supply chain of the industrial economy being improved based on less overhead. Therefore, the cost overhead is less than this model's other factors.

5.2. **Data computing time.** In Figure 9, the maximum optimization of the industrial economy relies on the supply chain obtained through PSO-induced CM for maximum cost-effective detection in the industrial supply chain model. The cost-effective connecting position is identified, and the overhead is considered for improving the sustainability of the industrial supply chain management for the instance $\frac{(Ind_1+Ind_2+\cdots+Ind_n)/3-PO^V}{F_V}$. In this model, product distribution and cost-effectiveness are processed in a balanced manner.

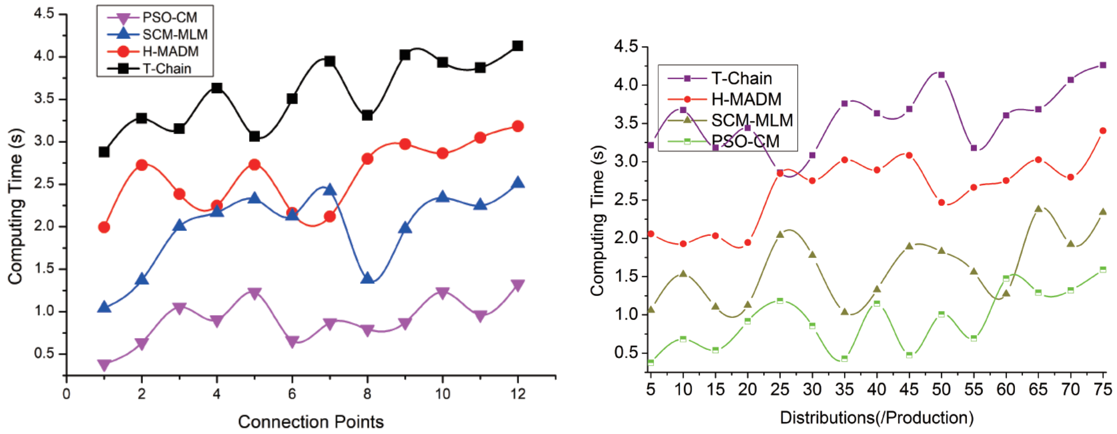

FIGURE 9. Data computing time comparisons

The productivity, distribution, and revenue are maintained for better standardization and identified the least cost-effective connecting position for each distribution. The industrial supply chain performs the maximum product distribution in which the PSO optimization satisfies less data computing time.

5.3. **Precision.** The proposed model improves the distribution precision using different conditional analyses. In the condition analysis process, the initial population using p_{ij} is required for verifying the distribution. Post the validation process, the cost overheads are suppressed using the F_V solutions. The F_V solutions are identified using the PO^V differentiation for its minimum and maximum derivatives. The position updates and connectivity improvements are analyzed in the repeated iterations for cost-effective distribution planning. Cases 2 and 3 are used for planning associated features for distribution and revenue. Using repeated iterations, the best-fit solution is filtered from the supply chain distribution from T to $(T+1)$. In this case, the population is updated from the new iteration, and the available Bfs_{ij}. However, the best-fit solution is used temporarily until a new position update is identified. Considering the variations between two successive iterations the precision is computed using $Product_{dist}$ value. Post this computation, the classification is performed to prevent precision drops due to redistributions. Therefore, the rescheduling is estimated over the varying distributions and connecting points. This enhances the distribution efficiency preventing multiple conditional validations in the local best solution (Refer to Figure 10).

5.4. **Distribution improvements.** Figure 11 presents the distribution improvements for the varying connecting points and distributions. As the connecting points increase, the variations in rescheduling are suppressed at the maximum local solution. This generates a large quantity of Bfs_{ij} over the available F_V; the iteration is considered before classification. Post the PO^V classification two conditions are analyzed for deciding over the precision. The precision is analyzed for the cost overhead and minimum cost-effectiveness. The cost-effectiveness for p_{ij} is estimated using Q improvements; the iteration is repeated for varying distributions. In the available iterations, the population for P_{ij} is varied for the jth supply verifying the revenue as discussed in the cases. The second condition analyzes the F_V, $\theta \geq T$ condition for which a complete distribution analysis is required. This is validated for T and $(T+1)$ iterations recurrently for improving the precision in distribution. The occurrence of both conditions reduces the best-fit solution and therefore the optimization is performed based on $C^{Ec}_{\min}$. In the new optimization $p_{ij}(T+1)$ is induced to

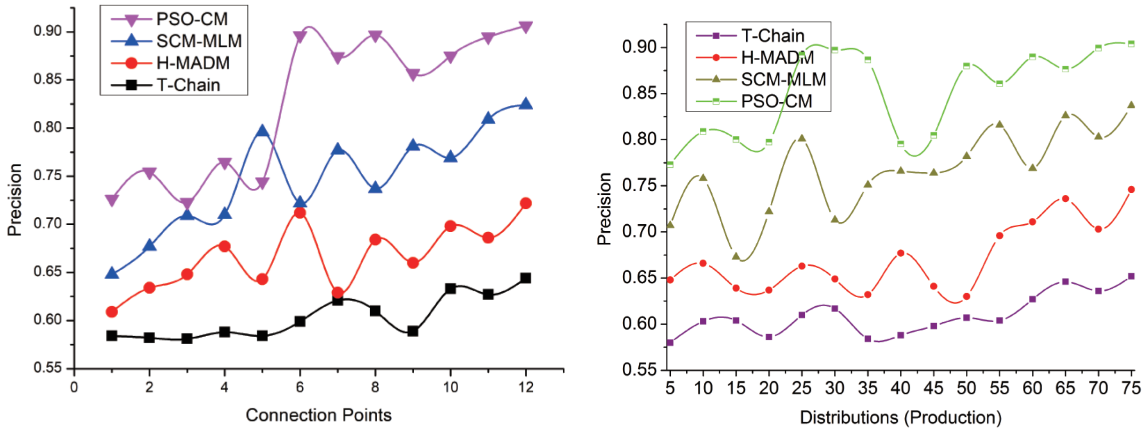

FIGURE 10. Precision comparisons

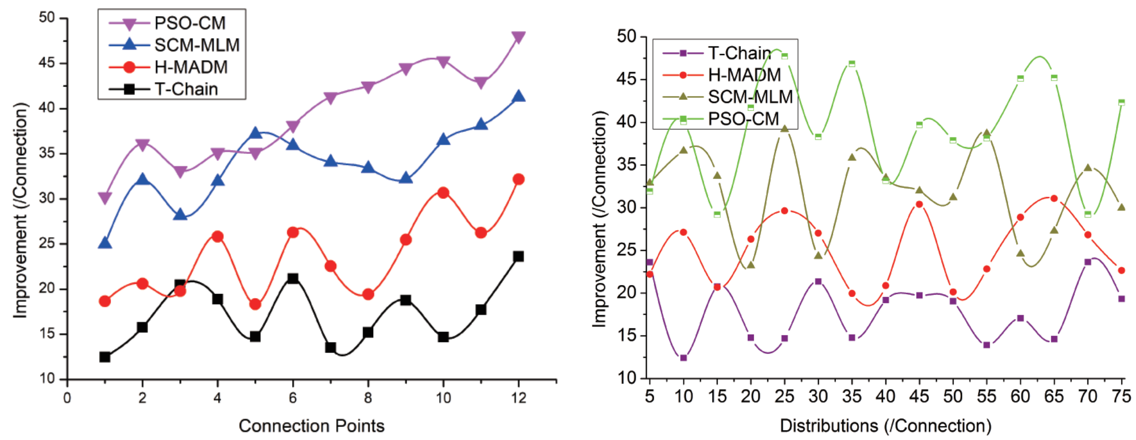

FIGURE 11. Distribution improvements comparison

prevent further suppressions or redistributions. Therefore, the distribution improvements are balanced at a high rate for the varying T and $(T+1)$.

5.5. **Connecting positions identified.** The comparative analysis for connecting positions identified is presented in Figure 12. The connecting position identification improves the Q and inturns the $Product_{dist}$. This is achieved using the latest position update of the supply chain; the position is identified using the final best solution. The final best solution is identified using $C_{\min}^{Ec}$ across multiple $(T+1)$ such that the population is improved. In the population update, the random integer adjustments are exploited for balancing the supply chain distributions. In the distribution process, the first set of iterations is required for identifying Bfs_{ij} under controlled $Cost_{Ovh}$. The consecutive iteration is required for identifying Fs_{ij} for the modified condition in SC_D. This modified condition includes classified PO^V for which the position updates are mandatory and hence cost-effective control is pursued. This is required for improving the SD_{ij} in T and $(T+1)$; the unique condition of $(1-q)$ is attained for achieving additional F_V. Therefore, the recurrent iterations are responsible for improving the position detection through periodic updates and classified PO^V. This is monotonously computed for the varying connecting points and distributions. Tables 3 and 4 present the comparative analysis results for the varying connection points and distributions.

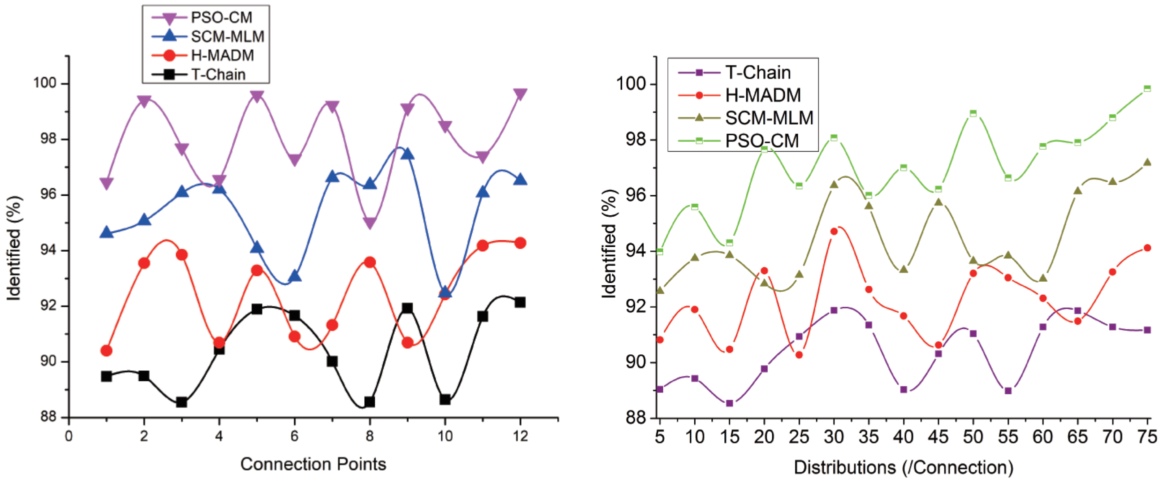

FIGURE 12. Connecting positions identified comparison

TABLE 3. Comparative analysis for varying connection points

Metrics	T-Chain	H-MADM	SCM-MLM	PSO-CM	Findings
Overhead (Repetitions/Point)	0.192	0.132	0.085	0.0371	9.92% Less
Computing Time (s)	4.1268	3.183	2.508	1.325	9.92% Less
Precision	0.644	0.722	0.824	0.9062	8.81% High
Improvement (/Connection)	23.62	32.17	41.25	48.031	7.84% High
Identified (%)	92.14	94.28	96.52	99.673	10.72% High

TABLE 4. Comparative analysis for varying distributions

Metrics	T-Chain	H-MADM	SCM-MLM	PSO-CM	Findings
Overhead (Repetitions/Point)	0.235	0.182	0.121	0.0613	11.8% Less
Computing Time (s)	4.2607	3.405	2.338	1.591	8.72% Less
Precision	0.652	0.746	0.837	0.9039	7.95% High
Improvement (/Connection)	19.32	22.66	29.97	42.314	9.17% High
Identified (%)	91.17	94.12	97.17	99.839	11.37% High

6. **Conclusion.** This article discussed the process of particle swarm optimization-induced connecting model for improving the distribution efficiency of industrial supply chain management. The proposed model addresses redistribution and delivery point connection issues through supportive decisions. The decisions are performed using selective population initialization across different swarm iterations. The cost-effective improvements are classified for the minimum and maximum position valued from which local best-fit solutions are extracted. Such solutions are revisited using the minimum cost effectiveness obtained from multiple connecting points for attaining one final solution. This final solution is retained until a new rescheduling in distribution is observed; the iteration is preceded using different fitness conditions for retaining the distribution precision. The proposed PSO-CM model achieves 11.8% less overhead, 8.72% less computing time, 7.95% high precision, 9.17% high improvement, and 11.37% high positions identified.

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