

# Information Management in the Logistics and Distribution Sector Using Metaheuristic Techniques

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## ABSTRACT

Information systems (IS) influence logistic and distribution management on sourcing, planning, delivery, and levels ranging from strategic operations to organizational strategy. Information management is a challenging task in logistics and distribution across the business. The supply chain has been increasingly accepted as a significant aid to cut costs and boost services. This paper proposes meta-heuristic techniques (MHT) for effective information management in logistics and distribution, from manufacturers to customers, security, a significant focus on collaboration of operations, co-operation, communication, and knowledge exchange across the supply chain. Modern organizations need advanced decision support systems focused on operative statistical modeling and solution methods and information and communication technology developments to adapt to the integration challenge. It suggests that metaheuristics can play an essential role in addressing complex logistical challenges from logistic architecture and management within the supply chain.

## KEYWORDS

Customer Logistics Management, Metaheuristic Techniques

## INTRODUCTION

The demand for businesses to find new ways to develop value and provide it for their consumers is rising ever more strongly in today's intensely dynamic global marketplace (Yavas & Ozkan-Ozen, 2020, Sgarbossa, et al. 2020, & Karaman, et al. 2020). The automotive sector starts to compete for demand on its goods on a global market. Service dimensions, quality, and cost have contributed significantly to the need to build more effective logistic structures than those used historically (Orjuela, et al. 2021 & Hu, et al. 2020). Moreover, logistics has evolved from a company to the business stage over the last two decades. Effective distribution control in the business and supply has been increasingly accepted. Active distribution strategy across business and supply chain has continually been recognized as a great contribution to the mission of cost savings and service development (Khalaf, et al. 2002, Ali & Mahmood, 2020, & Tayal, et al. 2020). In terms of logistics management, success must be accomplished throughout the supply chain, from the vendor to the customer, by the convergence of operations, collaboration, communication and knowledge exchange (Manogaran & Alazab, 2020). Modern organizations need innovative decision-making processes (DSS) focused on strong statistical

DOI: 10.4018/IJISSCM.305850

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models and solution methods and developments in information and communication technology in reaction to the challenge of integration (Su, et al. 2021).

Quantitative models and computer-based decision-making techniques play a significant role in today's corporate climate. In the fast-growing field of logistics administration, this is particularly so. Such computerized logistics systems may even have a huge effect on organizations on the decision-making process (Sankayya, et al. 2021 & Gupta, et al. 2021). There is an increasing desire from both industry and academia to use logistic management and logistics DSS to solve the challenges and problems presented by changes in the field. There have been several well-known optimization algorithms, and it is evident that most did not have the desired influence on the decisions on logistics problems architecture and optimization (Lv et al. 2020). In addition, specific strategies rely heavily on issues and require high expertise. The implementation of decision-making processes leads to difficulties that clash with quick performance in a rapidly changing environment. Any of the more common commercial packages currently use heuristic methods or thumb rules.

Metaheuristic optimization algorithm integrated logistical management methods can handle a complicated optimization problem that cannot be solved in the conventional optimization approach (Al-Turjman, 2020 & Jan et al. 2020). In these last decades, extensive studies have been carried out in heuristic techniques, which suggest new, effective techniques, including various metaheuristic methods for addressing difficult issues (Sennan et al. 2020). For that cause, a sophisticated logistics decision support system is required, which helps companies react rapidly to new obstacles and logistics management problems. However, developments are needed in the field of metaheuristics, which can efficiently react to complex problems (Thaseen et al. 2020). Metaheuristics allow users to settle on the system for certain parameters and settings, and then modelling techniques to evaluate system actions in the event of uncertainty can be introduced. In this sense, metaheuristics play a key role. They can quickly achieve a very good solution that can be modified and built effectively to cope with very difficult logistics issues. Due to the knowledge sharing, high scalability, low cost and efficiency of a single processor computer, distributed computing model have received much attention in recent years. The most prominent distributed computing model has arisen in the current scenario from cloud computing (Gao et al. 2020 & Goodarzian et al. 2020).

Generally, everything offers self-service, dynamically flexible and observable access on-demand to a common pool of capital with a guaranteed level of services to consumers. To provide guaranteed Quality of Service (QoS) to users, it is necessary that jobs should be efficiently mapped to given resources (Abbasi et al. 2020 & Osaba et al. 2020). If the desired performance is not achieved, the users will hesitate to pay. Therefore scheduling is considered a central theme in cloud computing systems.

This paper suggests Meta-Heuristic Technology (MHT) for cost reduction and boosting services in handling the information management system, which is the most difficult challenge in logistics and delivery around the business. This approach facilitates suppliers and consumers in partnering, working together, engaging and sharing information through the enterprise and the supply chain. Thus, this research explores innovative support mechanisms for decision-making based on operative mathematical modelling and approaches and information and communication technologies to overcome challenges in their integration.

The main contribution of this paper includes:

- Design of MHT for effective logistics management and distribution.
- Mathematical exploration of MHT and implementation of a solution-based genetic algorithmic approach.
- Observation of experimentation results and comparative analysis.

The remaining part of the paper includes the discussion on existing heuristics approaches on supply chain and logistics management. After this, a detailed explanation of the proposed model for information management in the logistic and distribution sector. Following this, the experimental

analysis and discussion have been carried out to validate the research. Finally, the summary of the report has been included with the future scope of the current work in it.

## **EXISTING HEURISTICS APPROACHES ON SUPPLY CHAIN AND LOGISTICS MANAGEMENT**

The problem of a sustainable, closed-loop network was addressed by Samadi et al. (2018), and three new heuristics are proposed. They argued that heuristic solutions had been developed for best performance via metaheuristic. Three heuristic devices are used to create an initial population to launch the metaheuristic techniques used recently and old using Genetic Algorithm (GA) and Red Deer Algorithm (RDA). Furthermore, algorithm parameters are tuned to boost algorithm efficiency with the Response Surface Method (RSM) approach.

Harpreet Kaur et al. (2018) suggested a competitive supply chain sourcing and logistical model. MILP (Mixed Integer Linear Problem) models and MINLP (Mixed Integer Non -Linear Problem) are proposed to include several real-time buyers and suppliers such as capacity, costs, emissions, and lead-times. They introduced the Heuristic (H-1) to address large-scale data problems. They often performed the T-test significance using 42 randomly generated data instances with important Big Data characteristics between maximum and heuristic approach. The quality and computational time of the solution were indeed encouraged.

To resolve the issue of the distribution network, for the first time, Mostafa Hajiaghahi-Keshteli et al. (2018) proposed a new programming approach that includes a two-level decision-making paradigm and stochastic programming known as bi-level stochastic programming. One of the key contributions of this research was concentrating on diverse methods to intelligently achieve optimum local and global problems. Five different fast heuristics and six different metaheuristics were used in this research to answer the distribution network challenge. Two modern hybrid metaheuristic algorithms had been developed to boost both new and old metaheuristic capabilities.

Sanjoy Kumar Paul et al. (2019) had built a model to create a recovery strategy after a sudden disturbance to minimize the disruptive consequences. They further suggested three heuristic solutions based on distribution delays and fractional losses arising from a sudden disturbance. Eventually, numeric tests were performed to test the suggested intervention models. The model has been scenario-based analyzed, and the effects of a sudden transportation disturbance analyzed under three disruption scenarios. The efficiency of the given heuristics was therefore contrasted with the generalized gradient procedure.

Yasemin Kocaoglu et al. (2020) introduced a novel modified genetic algorithm known as 'Distribution Strategy Selection and Vehicle Routing Hybrid Algorithm' (DSSVRHE). They were aimed to bring a new hybrid approach to solve a mixed supply network issue that efficiently integrates three critical supply methods. Compared with the optimization methods, the effects of the hybrid algorithm was given the best. The mathematical analysis validated the efficiency of the hybrid algorithm. Their proposed approach proved its excellence to reduce logistics cost of supply chain and computing time through computational performance.

A method of solving the caught position-routing problem (CLRP) has been defined by Fadoua Oudouar et al. (2020) to minimize vehicle distribution distances. It could identify depots, attribute one depot to each customer and decide routes. To detect the deposits and assign consumers to stores, they used a self-organizing map (SOM). The self-organizing map with two-layer, unattended, and efficient learning mechanism in clustering. The routing problem was determined by the Clarke and Wright technologies. The findings showed higher success and reliability in large-scale solving.

Abdirad et al. (2021) proposed a dynamic vehicle routing problem (DVRP) to Minimize transport costs while serving customer requirements from a common depot without exceeding the capacity limit of each vehicle. Experimental results for different problem sizes have been designed. The results of the analysis show the efficacy of the proposed algorithm.

Based on the above survey, since the existing methods are not managing the information, the methods effectively boost the services. It is identified that there is a technological gap in information management for improved performance. Therefore, this paper proposes the most complex logistics and business supply challenge for meta-heuristic technology (MHT) to reduce costs and boost services in managing the information management system. The approach makes partnering, cooperating, engaging and sharing information across the company and supply chain easier for suppliers and consumers. This research explores innovative decision-making mechanisms based on operational mathematical modelling, approaches and information systems to overcome integrative challenges.

## PROPOSED SYSTEM

The proposed system focuses on the intelligent logistic information management system using meta-heuristic techniques. The proposed system minimizes the costs and improves services by handling IT management's structure the most challenging logistics and market problems by meta-heuristic technology (MHT). It makes it easy for vendors and customers to collaborate, interact, interact and exchange company-wide details. To solve integrative problems, this study examines novel methods for decision making focused upon the operational, statistical modelling, approaches and knowledge systems. Logistic information is not limited to a single unit or module of the entire supplychain network; from the supplier unit to the customer, the logistics information management system undergoes various tasks and services.

Figure 1 demonstrates the logistic information flow diagram for the information management module in the logistics and distribution network of the supply chain network. The free and effective operation of the logistics system includes the planning of many tasks such as supplier identification, product design, logistics procurement, production process life cycle, logistics network architecture, products transport, warehouse and inventory management, complete information and communication system, logistics acquisition, delivery logistics, and so on. As seen in figure 1, the information flow starts with the supplier unit. It keeps processing at each intermediate level, including production units, inventory management unit at warehouses, retailers, outlets, supermarkets, etc. Then, it stops at each customer unit. After this, reverse logistics and corresponding information management flow happens. The following figure 2 gives a detailed structure of the logistics and distribution sector.

The information management system of the supply chain network for logistic and distribution begins with the search for functional requirements. This information can assist the material requirement planning at the supplier unit. The material requirement planning integrates the production unit and inventory warehouse along with transportation since it includes procurement, production and distribution. Another aspect of a logistic information management system is named demand requirement planning. Since both planning strategies interconnect each other, the information flow in the logistic information management system must be optimized to minimize the cost (including

Figure 1. Logistics Information Flow in Supply Chain Network

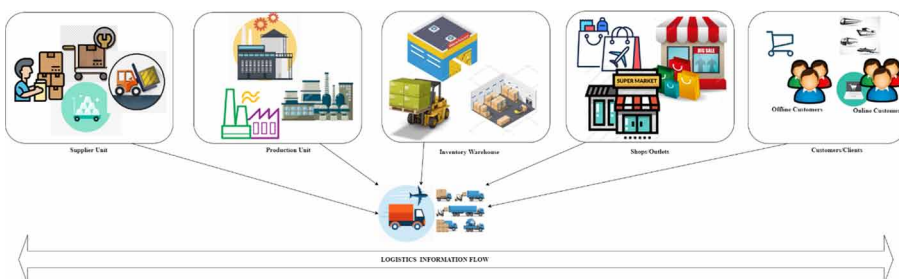
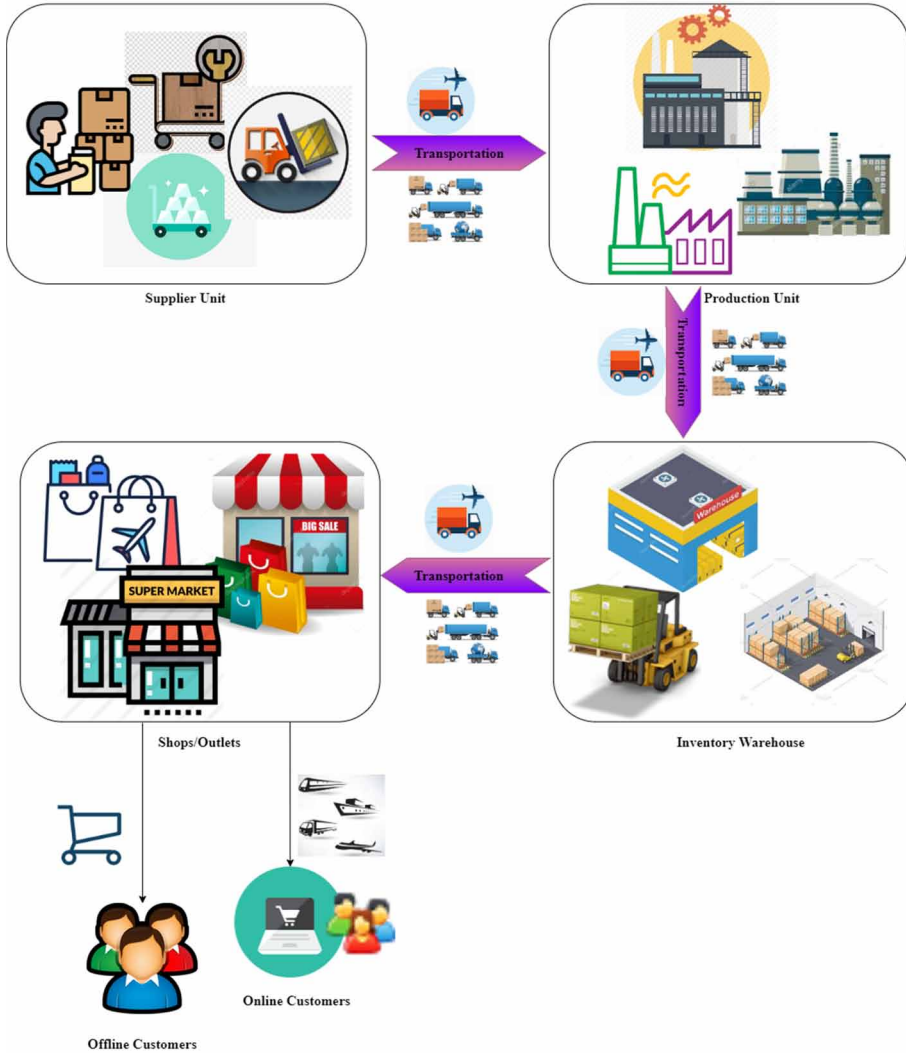


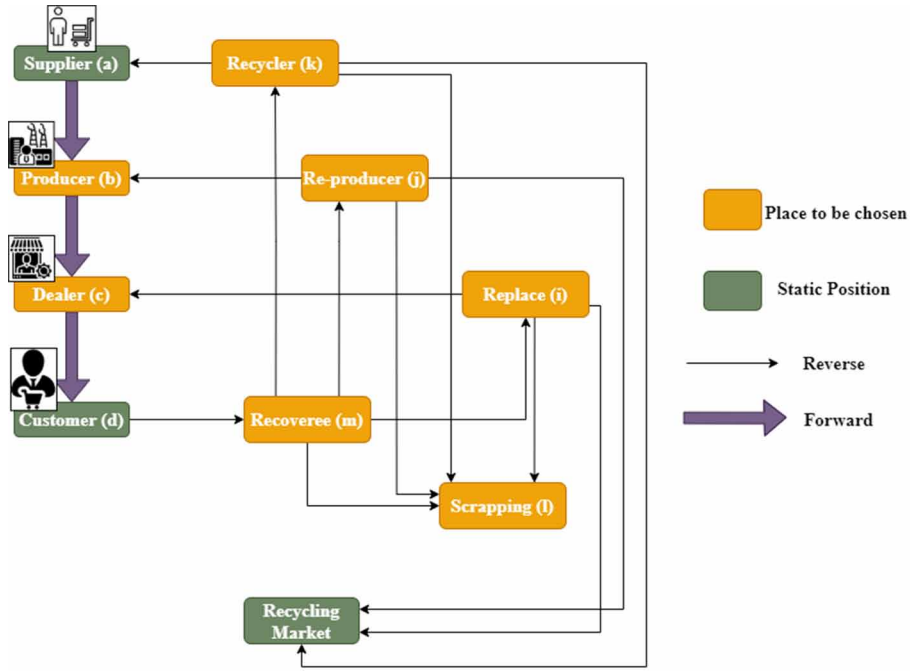
Figure 2. Basic Structure of Logistic and Distribution Sector



procurement cost, production cost, transportation cost, inventory warehousing cost, etc.) and improve the logistics services.

This research hypothesis has been formulated by generating three heuristics for solving the Multi-Integer Linear Programming (MILP) model with both forward logistics and reverse logistics that illustrates the logistic and distribution sector, as shown in figure 3. The provided MILP model with ten echelons for a closed-loop network architecture presents a treatment method, considering four types of networks termed reverse network. This includes recovering, reproducing, recycling and scrapping. Each echelon in this figure has participated in the forward logistics. Among these, the supplier, producer, dealer, and customer have participated in forwarding logistics. The model developed pre-assumes certain factors, such as the client demand should be met, the number of facilities and their possible sites in each echelon, the absence of flows among the same facilities, the number of finished products sent to collectors is a fraction of customers' demands and the qualitative allocation of the treatment centre. The research challenge in this logistics and distribution sector in the supply

Figure 3. MILP model for Logistic and Distribution Sector



chain network is deciding the number of goods to produce on each site, the consumer assignment to dealers and collectors, and the materials' flow.

Based on the study, this model develops the three objective functions referred to as Overall Network Cost, Cost from Environment Factors, and Capacity from Factors. Table 1 gives the basic parameters and their definitions for the following objective functions. The given below shows the first objective function:

$$\begin{aligned}
 \min OF1 = & \sum_b F_b^{ec} \cdot C_b + \sum_E \sum_{e_f} F_{e_f}^{ec} \cdot C_{e_f} \\
 & + \sum_a \sum_b \cdot P_a^c \cdot f_{ab}^p + \sum_b Mm_b^c \cdot N^p \\
 & + \sum_E \sum_{E'} \sum_{e_f} \sum_{e_f'} T_{e_f e_f'}^c \cdot f_{e_f e_f'}^p + \sum_c \sum_d A_{cd}^c \cdot D_d \cdot C'_{cd} \\
 & + \sum_d \sum_m \left( R_{dm}^c + H_m^c \right) \cdot D_d \cdot C'_{dm} \cdot \mu_d - S^c \cdot \left( \sum_i \sum_c f_{ic}^p \right) \\
 & - S^m \cdot \left( \sum_j \sum_b f_{jb}^p \right) - S^r \cdot \left( \sum_k \sum_a f_{ka}^p \right) - S^s \cdot \left( \sum_E \sum_{e_f} \sum_m \zeta_E \cdot f_{e_f m}^p \right)
 \end{aligned} \quad (1)$$

First-ever target minimizes the cumulative network cost and as seen in Equation 1. The first and second terms seem to be the static opening cost for installations in this respect. In terms of the third to the eighth overview, the costs of procurement, processing, handling, transport, allocation, and retrieval are included. The last four operations represent the effect of reusing goods at processing facilities, the distribution of products recycled or reproduced, and the distribution of standard products to cost savings.

Table 1 helps find the parameter definition for the notations used in equation 1. In addition, the second objective is to quantify the environmental effects of the network. Thus, formulated the objective function as expressed in equation 2:

Table 1. Parameter - Definition Set 1

Parameters	Definitions
$a$	Supplier Set, $a \in \{1, 2, 3, \dots, U\}$
$b$	Producer Set, $b \in \{1, 2, 3, \dots, V\}$
$c$	Dealer Set, $c \in \{1, 2, 3, \dots, W\}$
$d$	Customer Zone Set, $d \in \{1, 2, 3, \dots, X\}$
$i$	Replace Center Set, $i \in \{1, 2, 3, \dots, I\}$
$j$	Re-producer Set, $j \in \{1, 2, 3, \dots, J\}$
$k$	Recycler Set, $k \in \{1, 2, 3, \dots, K\}$
$l$	Recoveree or Collector Set, $l \in \{1, 2, 3, \dots, L\}$
$m$	Scrappers Set, $m \in \{1, 2, 3, \dots, M\}$
$E$	Echelons $E \in \{i, j, k, l, m\}$
$E'$	Echelons Superset, $E' \in \{a, b, c, d, i, j, k, l, m\}$
$e_f$	Facility Set for Echelons $E, e_f \in \{1, 2, 3, \dots, E_F\}$
$e'_{f'}$	Facility Set for Echelons $E', e'_{f'} \in \{1, 2, 3, \dots, E'_{F'}\}$

$$\begin{aligned}
 \min OF2 = w_t^p & \\
 & \left[ \sum_b I_b^{en} \cdot C_b + \sum_E \sum_{e_f} I_{e_f}^{en} \cdot C_{e_f} + \sum_b U_b^{ei} \cdot N^p + \sum_E \sum_{E'} \sum_{e_f} \sum_{e'_{f'}} T_{e_f e'_{f'}}^{ei} \cdot f_{e_f e'_{f'}}^p \right. \\
 & \left. + \sum_E \sum_{E'} \sum_{e_f} \sum_{e'_{f'}} H_{e_f}^{ei} \cdot f_{e_f e'_{f'}}^p + \sum_d \sum_m \left( H_m^{ei} + H_{dm}^c \right) \cdot D_d \cdot C'_{dm} \cdot \mu_d + \sum_m \sum_l I_l^{ei} \cdot f_{ml}^p \right. \\
 & \left. - S^{ec} \cdot \left( \sum_i \sum_c f_{ic}^p \right) - S^{em} \cdot \left( \sum_j \sum_b f_{jb}^p \right) - S^{er} \cdot \left( \sum_k \sum_b f_{kb}^p \right) \right. \\
 & \left. - w_s^p \left( \sum_b P_b^H \cdot N^p \cdot \left( 1 - d_b^p \right) \right) \right] \quad (2)
 \end{aligned}$$

In equation 2, the objective function has been formulated to minimize environmental impacts. In the first and second words, these environmental consequences related to opening facilities are added. The next five elements reflect the effect of the production, transport, manipulation/handling and scrapping/disposal of goods on the environment. The environmental advantages of end of life goods are the next three terms. The very last team encompasses the damage that the goods inflict.

Table 2. Parameter – Definition Set2

Parameters	Definitions
$OF1$	Objective Function for minimizing cost
$F_b^{ec}$	Establishing Cost of Manufacturer $b$ (fixed)
$C_b$	Constant takes 0 or 1; 1 when $b$ is to be established and 0 otherwise
$F_{e_f}^{ec}$	Establishing Cost of Echelon Set $e_f$ (fixed)
$C_{e_f}$	Constant takes 0 or 1; 1 when $e_f$ is to be established and 0 otherwise
$P_a^c$	Raw Materials Purchasing Cost from Supplier $a$
$f_{ab}^p$	Product Flow from $a$ to $b$
$M_b^c$	Unit Cost of Production at $b$
$N^p$	Number of Products Produced at $b$
$T_{e_f e_{f'}}^c$	Cost of Transportation per unit from $e_f$ to $e_{f'}$
$f_{e_f e_{f'}}^p$	Product Flow from $e_f$ to $e_{f'}$
$A_{cd}^c$	Allocation Cost of a Customer Zone $d$ by dealer $c$
$D_d$	Customer Demand from Zone $d$
$C_{cd}'$	Constant takes 0 or 1; 1 when $d$ assigned to $c$ and 0 otherwise
$R_{dm}^c$	Collection Cost of End-of-Life Products from $d$ to $m$
$H_m^c$	Handling Cost per unit at $m$
$C_{dm}'$	Constant takes 0 or 1; 1 when $d$ assigned to $m$ and 0 otherwise
$\mu_d$	Used Product Fraction returned from $d$
$S^c$	Cost Savings from replacement

continued on following page

Table 2. Continued

Parameters	Definitions
$f_{ic}^p$	Product Flow from $i$ to $c$
$S^m$	Cost Savings from Re-production
$f_{jb}^p$	Product Flow from $j$ to $b$
$S^r$	Cost Savings from Recycling
$f_{ka}^p$	Product Flow from $k$ to $a$
$S^s$	Selling Price of the End-of-Life Product at $l$
$\zeta_E$	Shipped Products Fraction from $E$
$f_{e_fm}^p$	Product Flow from $e_f$ to $m$

Table 3 extends table 1 and 2 by giving the definitions of the parameters included in equation 2 and not included in table 1 and table 2. The following equation defines the objective to be maximized based on social impacts on current logistics and distribution, as seen in the MILP model:

$$\max OF3 = w_o^p \left[ \begin{aligned} &\sum_b O_b^N \cdot C_b + \sum_E \sum_{e_f} O_{e_f}^N \cdot C_{e_f} + \sum_b \frac{O_b^{N^v} \cdot N^p}{\Psi_b} + \sum_c \sum_b \frac{O_c^{N^v} \cdot f_{bc}^p}{\Psi_c} \\ &+ \sum_m \sum_d \frac{O_m^{N^v} \cdot c'_{dm} \cdot \mu_d \cdot D_d}{\Psi_m} + \sum_E \sum_{e_f} \sum_m \frac{O_{e_f}^{N^v} \cdot f_{me_f}^p \cdot n_m^E}{\Psi_{e_f}} \end{aligned} \right] - w_{LD}^p \left[ \begin{aligned} &\sum_b LD_b^c \cdot C_b + \sum_E \sum_{e_f} LD_{e_f}^c \cdot C_{e_f} + \sum_c \sum_b \frac{LD_b^{N^v} \cdot f_{bc}^p}{\Psi_c} \\ &+ \sum_m \sum_d \frac{LD_m^{N^v} \cdot C'_{dm} \mu_d \cdot D_d}{\Psi_m} + \sum_E \sum_{e_f} \sum_m \frac{LD_{e_f}^{N^v} \cdot f_{me_f}^p \cdot \eta_m^E}{\Psi_{e_f}} \end{aligned} \right] \quad (3)$$

The permanent work prospects have been provided in the first two terms of the formula. These jobs are seen in the third to sixth terms. Furthermore, when a facility uses its maximum potential more employees are used, and, on the other hand, fewer workers are used where reduced capacity is available. The next six criteria reflect damage to the work sustained during either the construction of structures or the fabrication and handling of items.

Table 4 describes the remaining parameter definitions for equation 3, which extend the previous tables. All the objective functions aim at the sustainable integrated supply chain network with efficient

Table 3. Parameter - Definition Set 3

Parameters	Definitions
$OF2$	Objective Function for minimizing the environmental impacts
$w_t^p$	Weight Factor assigned to transportation and initial emissions of $OF2$ elements
$I_b^{en}$	Impacts of environmental factors while establishing $b$
$I_{e_f}^{en}$	Impacts of environmental factors while establishing $e_f$
$U_b^{ei}$	Impacts of environmental factors in producing unit product at $b$
$T_{e_f e_{f'}}^{ei}$	Impacts of environmental factors in transporting materials for a unit product from $e_f$ to $e_{f'}$
$H_{e_f}^{ei}$	Impacts of environmental factors in handling unit product at $e_f$
$H_m^{ei}$	Impacts of environmental factors in handling unit product at $m$
$T_{dm}^{ei}$	Impacts of environmental factors in transporting materials for a unit product from $d$ to $m$
$I_l^{ei}$	Impacts of environmental factors while establishing $l$
$f_{ml}^p$	Product Flow from $m$ to $l$
$S^{ec}$	Environmental Benefits for a unit product in replace
$S^{em}$	Environmental Benefits for a unit product in production
$S^{er}$	Environmental Benefits for a unit product in recycling
$w_s^p$	Weight Factor assigned to scrapping products of $OF2$ elements
$P_b^H$	Hazardous Products Fraction at $b$
$d_b^p$	Damaged Products Fraction at $b$

logistic and distribution management. These three equations must be formulated under several constraints that may occur while concerning real-time implementation. The following statistically expresses these constraints:

$$\sum_a f_{ab}^p = \sum_c f_{bc}^p \text{ for all } b \quad (4a)$$

Table 4. Parameter – Definition Set 4

Parameters	Definitions
$OF3$	Objective Function for maximizing social impacts
$w_O^p$	Weight Factor assigned to created job opportunities of $OF3$ elements
$O_b^N$	Job Opportunities (fixed) number at $b$
$O_{e_f}^N$	Job Opportunities (fixed) number at $e_f$
$O_b^{N^v}$	Job Opportunities (variable) number at $b$
$\Psi_b$	Capacity at $b$
$O_c^{N^v}$	Job Opportunities (variable) number at $c$
$\Psi_c$	Capacity of $c$
$O_m^{N^v}$	Job Opportunities (variable) number at $m$
$\Psi_m$	Capacity of $m$
$O_{e_f}^{N^v}$	Job Opportunities (variable) number at $e_f$
$\eta_m^E$	Used Product Fraction from in, where
$\Psi_{e_f}$	Capacity of $e_f$
$w_{LD}^p$	Weight Factor assigned to lost days of workers of $OF3$ elements
$LD_b^c$	Cost of lost days from damages of work at $b$
$LD_{e_f}^c$	Cost of lost days from damages of work at $e_f$
$LD_b^{N^v}$	Number of lost days due to works' damage at $b$
$LD_m^{N^v}$	Number of lost days due to works' damage at $m$
$LD_{e_f}^{N^v}$	Number of lost days due to works' damage at $e_f$

$$\sum_b f_{bc}^p = \sum_d D_d \cdot C'_{cd} \text{ for all } c \quad (4b)$$

The above constraints demand that the flow of products from the supplier to the producer must be equal to the flow of products from producer to dealers for all producers. This constraint means that all the resources utilized without any loss. Equation 4a expresses this constraint, and 4b expresses the constraint for all dealers, where the flow of products from producer to dealer must be satisfied with all the demands from the customer:

$$\sum_{e_f} f_{me_f}^p = \sum_d \eta_m^E \cdot C'_{dm} \cdot \mu_d \cdot D_d \text{ for all } m, E \quad (5a)$$

$$\sum_d C'_{dm} \cdot \mu_d \cdot D_d \leq \eta_m \cdot C_m \text{ for all } m \quad (5b)$$

Equation 5a defines the constraint that can be considered for the resource allocation and handling at the collector echelon. This constraint ensures the effective handling of reverse logistics with significant allocation. Product distribution through a collector must be permitted if it is operational and has adequate power as limited in Equation 5b:

$$\sum_a f_{ka}^p = (1 - \zeta_k) \cdot \sum_m f_{mk}^p \text{ for all } k \quad (6a)$$

$$\sum_b f_{jb}^p = (1 - \zeta_j) \cdot \sum_m f_{mj}^p \text{ for all } j \quad (6b)$$

$$\sum_c f_{ic}^p = (1 - \zeta_i) \cdot \sum_m f_{mi}^p \text{ for all } i \quad (6c)$$

The constraints expressed in equation 6a, 6b, and 6c demand the significant management of products shipped from a supplier, producer, dealer through replacer, reproducer, and recycler, respectively. Where,  $r_k$  is the shipped fraction from the replacer,  $r_j$  is the shipped fraction from the reproducer and  $r_i$  is the shipped fraction from the recycler:

$$N^p = \sum_a f_{ab}^p \leq \Psi_b \cdot C_b \text{ and } \sum_b C_b \leq \max_b \text{ for all } b \quad (7a)$$

$$\sum_b f_{ab}^p \leq \eta_a \text{ for all } a \quad (7b)$$

$$\sum_c C'_{cd} = \sum_m C'_{dm} = 1 \text{ for all } d \quad (7c)$$

In the presumption that each producer will indeed produce products if opened and has idle capacity, the number of products produced by a producer can be determined by equation 7a. As seen in Equation 7b, the amount of goods received by each provider is constrained by its capacity. Equation 7c limits the allocation with just one dealer and retrieval centre for each customer area:

$$\sum_c f_{bc}^p \leq \Psi_c \cdot C_c \text{ for all } c \quad (8a)$$

$$\sum_{me_f} f_{me_f}^p \leq \Psi_{e_f} \cdot C_{e_f} \text{ for all } e_f \quad (8b)$$

Equation 8a shows the constraint that the product flow from producer to dealer must be carried out concerning their capacity. Similarly, equation 8b constraints the product flow from the recoveree to all the facility centres in  $e_f$ . Generally, whenever the respective facility works and thus has sufficient capacity seems to be the flow of products through a facility necessary, and each facility in every echelon has been restricted to predefined numbers.

The suggested MHT-based logistics and distribution field tackles the sustainable structure of the closed-loop supply chain by three heuristics methods for creating an initial metaheuristic population. Furthermore, a new and old metaheuristic approach is used to tackle the problem. This proposal uses three heuristics (H1, H2, H3) for these binary variables to select distribution centres, stores, recoveree centres and recyclers.

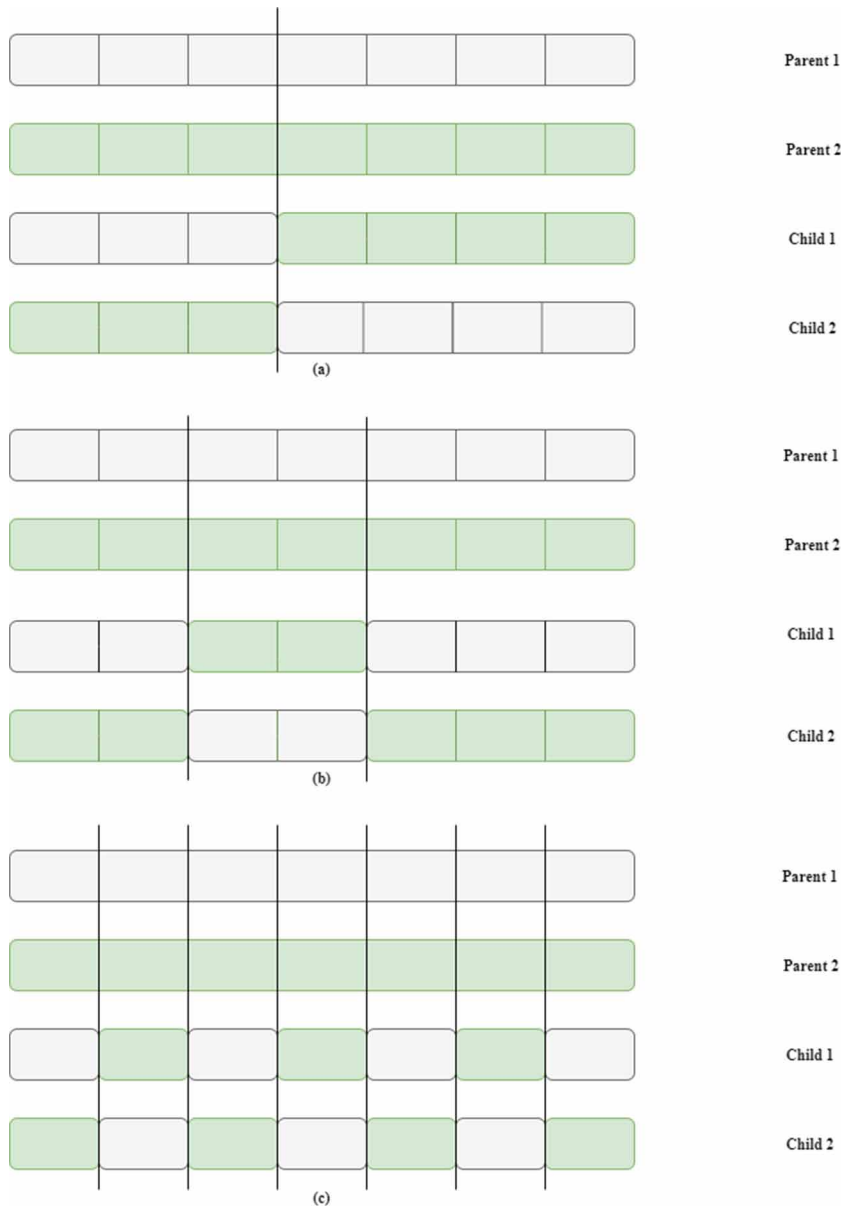
- H1:** The facility centres are chosen according to their maximum size given each of the above facilities' capability. Thus, services are chosen depending on the maximum measurements of the original population.
- H2:** By considering the fixed costs of opening the listed installations, the initial population is specified. In the first initial strategies, the installations are chosen based on the minimum fixed opening costs.
- H3:** The facilities have been chosen on the basis of minimal transportation costs of summations. In all facilities, centres with minimal cost of transportation are thus chosen earlier for the initial metaheuristic populations.

## SOLUTION APPROACH USING GENETIC ALGORITHM (GA)

Genetic algorithms process replicates biological selection processes, which indicates species able to sustain, produce offspring go to the future, who could evolve to external demands. Simply put, they mimic 'the fittest sustainability' for each of the next-generation conflict resolutions. The solution approach for these can be applied with several bio-inspired optimization algorithms. This study uses the genetic algorithm that includes the three phases of mutation, crossover, and reproduction. The mutation strengthens the intensification properties primarily and relies on the diversification features to explore the future region of the crossover. More explanation on crossover and mutation operators are taken into account below. Two new solutions are created in the crossover operator using two parental solutions. Three forms of crossover operators are used in this analysis. The three varies of single-point, double and uniform crossovers are shown in Figure 4. These methods have been figured out using the first step of random numbers from the random key approach to solution representation.

Figure 4a shows how the single-point crossover works, where the parent organism string is being crossed by a crossover point. Every information after that are swapped between the two parent species within the entity sequence/chromosomes, characterizes the positional bias. The double crossover or two-point crossover has been illustrated in equation 4b. The individual chromosomes (strings) are picked from two arbitrary points, and at these points, the genetic material appears interchanged. A

Figure 4. Structure of Crossover Operations (a) Single-Point Crossover (b) Double Crossover (c) Uniform Crossover



random selection of each gene (bit) is made for a uniform crossover from one of the parent chromosomal genes, as seen in Figure 4c.

Another GA operator that works here is mutation; to generate some new ones (offspring), it searches and considers the neighbours around a percent of solutions (parents). The three procedures for this operator are swap, reversion and insertion in this respect. Then it can lead to a better or decent solution by crossing two good solutions. The chance of the offspring being successful is high because the parents are good. Since descendants are unsafe (poor solution), the selection has been eliminated in the next iteration.

## EXPERIMENTAL ANALYSIS AND DISCUSSION

First of all, the criteria and the test problems were evaluated in this section. To increase the efficiency of the algorithms is used the response surface process. The various approaches were tested according to multiple parameters, and several experiments have been recommended to analyze the behaviour of heuristics and metaheuristics. All the tests were conducted with a laptop configured Core 2 Duo-2.26 GHz processor. The accompanying codes were written in Java and constructed by Microsoft Visual Studio 2019 version.

Initial criteria were structured to create a proposal, and the number of positions in each echelon reveals the problem complexity explicitly. The problems are then categorized into three decks labelled as small, medium and high, to investigate the exact scale of the problem. Six random issues were produced on each level. There are, therefore, 18 test problems. Normal distribution initializes consumer specifications with the set (100, 20). Figure 5 shows the values obtained for 9 test problems chosen alternatively, out of these 18 test problems. The following evaluation results find the feasibility of the proposed model.

The computation time analysis result is shown in Figure 6 for all three heuristics. From the 18 research problems, nine were selected alternatively for the illustration of the results. The results showed that the proposed model with GA resulted in the highest computation efficiency with the least computation time. Among these, the H1 had given the lowest computation time.

Figure 5. Objective Function Values for Chosen Testing Problems (a) OF1 (b) OF2 (c) OF3

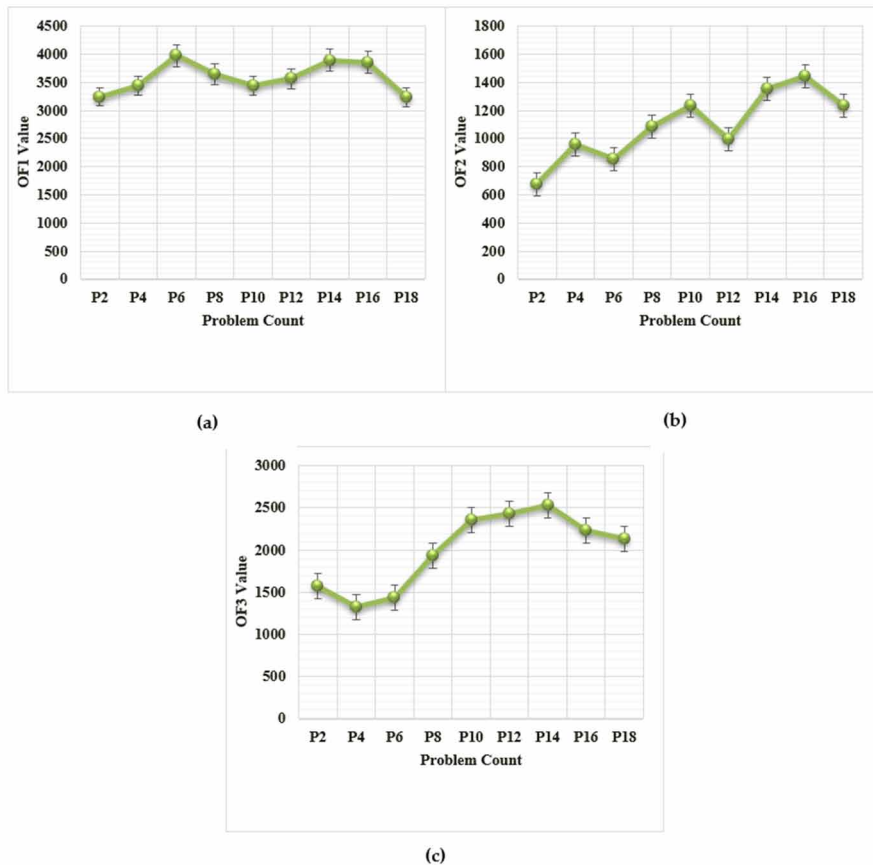
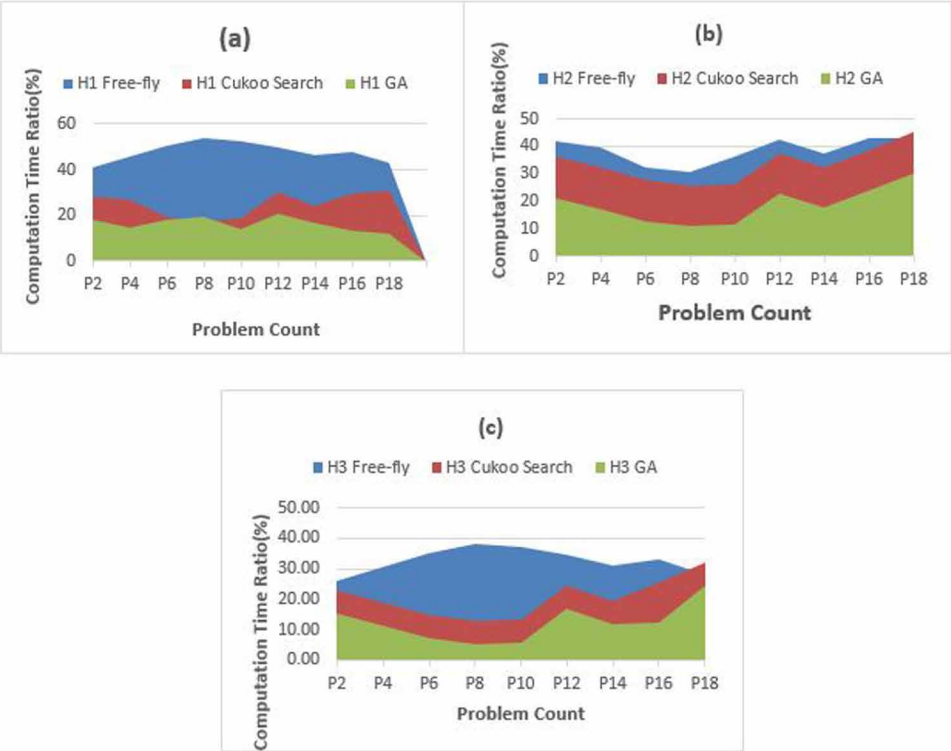


Table 5. Computation time for the H1, H2, and H3 in Different problem count

Problem Count	H1			H2			H3		
	Free-fly	Cukoo Search	GA	Free-fly	Cukoo Search	GA	Free-fly	Cukoo Search	GA
P2	41.18	28.17	18.35	41.78	36.09	21.09	25.96	22.95	15.31
P4	45.54	26.86	14.77	39.84	32.23	17.23	30.32	19.09	11.45
P6	50.53	19.45	17.79	32.53	27.77	12.77	35.31	14.63	16.99
P8	53.56	17.53	19.76	30.51	25.76	10.76	38.34	12.62	14.98
P10	52.42	18.71	13.76	36.58	26.45	11.45	37.20	13.31	15.67
P12	49.61	29.93	20.72	42.39	37.58	22.58	34.39	24.44	16.80
P14	46.25	24.23	16.75	37.37	32.56	17.56	31.03	19.42	11.78
P16	48.12	29.87	13.55	42.86	38.78	23.78	32.90	25.64	12.23
P18	43.28	30.62	12.06	43.24	45.32	30.32	28.06	32.18	24.54

Figure 6. Computation Time Analysis for (a) H1; (b) H2; (c) H3



Besides, half of the potential units was determined for each step for the full number of units required. Random numbers are calculated for the establishments' fixed costs of opening and the total net expense of sourcing, making, storing and shipping a commodity brought back to the respective point of the forward chain. It was necessary to balance each step with the setting of the parameters in each algorithm for improving the algorithm performances. To determine the quality of feasible adaptive solutions, the study of method solutions has been carried out using four evaluation criteria. Therefore, the four efficiency estimation measurements used in this paper are outlined in the following.

The suggested metrics are used to perform the study to determine the feasibility and reliability algorithms. They are split into four variants for two presented metaheuristics in conjunction with the three suggested heuristic procedures under GA and other bio-inspired algorithms. Figure 7 plots the percentage deviation of the metric 'Diversification' evaluated for three heuristics formulated in this research in solving 18 problems. This metric evaluates the measure of infeasible solution spread. Among three heuristics, heuristics 2 in GA shown the least percentage deviation for the highest diversification compared to other optimization algorithms.

Figure 8 illustrates the results obtained for three chosen heuristics concerning the percentage deviation of the metric dominance ratio. The dominance ratio measures how well the algorithm solution dominates the solutions of other algorithms. Figure 8 evaluates the deviation in these results by taking the difference between the algorithm solution and the best solution and dividing it by the best solution.

Figure 7. Percentage Deviation (PD) of the Performance Metric 'Diversification' for (a) H1; (b) H2; (c) H3

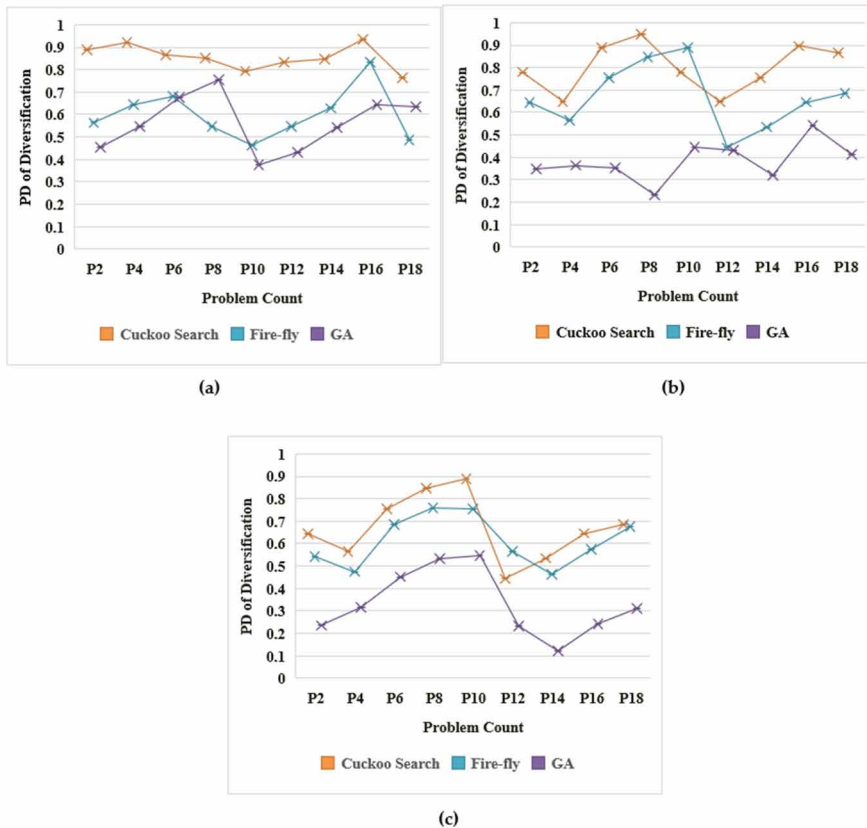
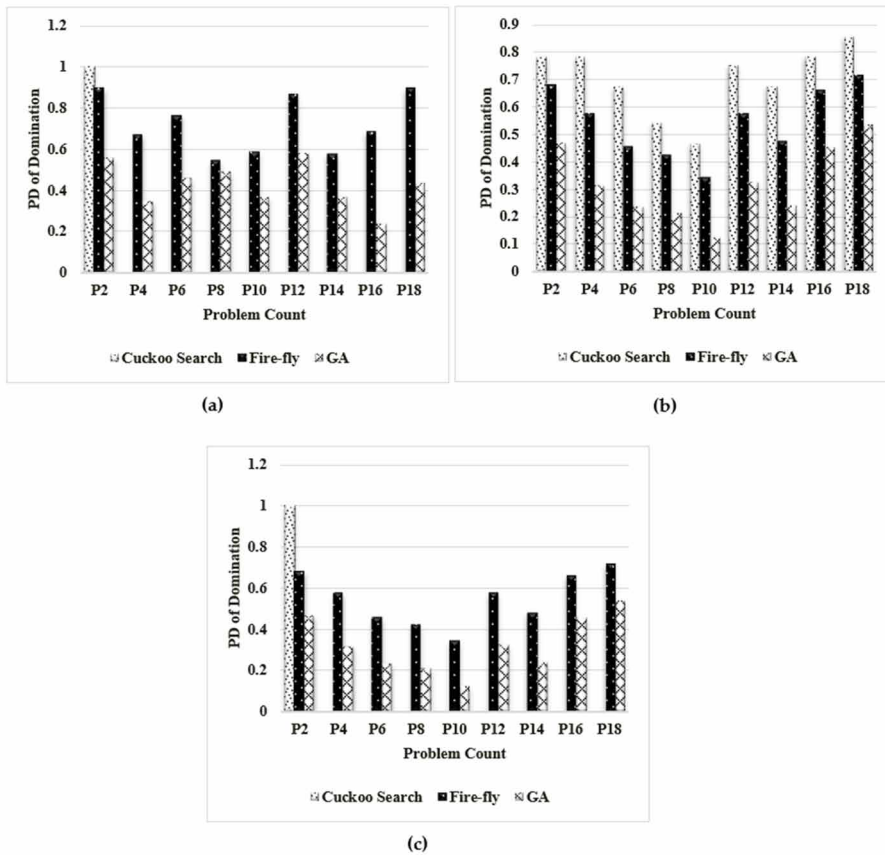


Figure 8. Percentage Deviation of the Performance Metric 'Dominance Ratio' for (a) H1; (b) H2; (c) H3



All the results for various performance metrics were given the optimum performance for the proposed MILP model, which demonstrated the real-time logistics flow in the supply chain network. The efficiency of the optimization algorithm assured that the economic, environment friendly, and socially acceptance of the logistics and distribution management system with better information flow maintenance. In general, the research study observed that the meta-heuristics techniques for information management in the logistics and distribution sector could assist the decision support systems in the supply chain network.

## CONCLUSION

This paper indicates the most challenging logistics challenge in the sector for Meta-Heuristic Technology (MHT) for cost savings and the boosting of services in maintaining the knowledge management infrastructure. This strategy encourages collaboration, interaction, involvement, and knowledge exchange through the business and supply chain between supplies and customers. This knowledge formed the MILP model to solve a sustainable issue in the closed-loop supply chain network by presenting some new real-world hypotheses. This study established three good heuristics to solve the proposed problem. Different efficiency measurements were analyzed and tailored for the proposed MILP model, displaying the real-time supply chain network. The maximum algorithm performance guaranteed that the logistics and distribution management system is economically, environmentally

sustainable and socially appropriate with better maintenance. The research study generally showed that meta-Heuristics in the logistics and distribution field could assist decision-making support structures in the supply chain network. In the future, intelligent decision making using artificial intelligence is planned to be integrated with this proposed model.

## **FUNDING AGENCY**

This research received no specific grant from any funding body in the public, commercial, or not-for-profit sectors.

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