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# Multi-echelon supply chain network modelling and optimization via simulation and metaheuristic algorithms

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**Abstract.** An important problem in today[s industries is the cost issue, due to the high level of competition in the global market. This fact obliges organizations to focus on improvement of their production-distribution routes, in order to find the best. The Supply Chain Network (SCN) is one of the, so-called, production-distribution models that has many layers and/or echelons. In this paper, a new SCN, which is more compatible with real world problems is presented, and then, two novel hybrid algorithms have been developed to solve the model. Each hybrid algorithm integrates the simulation technique with two metaheuristic algorithms, including the Genetic Algorithm (GA) and the Simulated Annealing Algorithm (SAA), namely, HSIM-META. The output of the simulation model is inserted as the initial population in tuned-parameter metaheuristic algorithms to find near optimum solutions, which is in fact a new approach in the literature. To analyze the performance of the proposed algorithms, different numerical examples are presented. The computational results of the proposed HSIM-META, including hybrid simulation-GA (HSIM-GA) and hybrid simulation-SAA (HSIM-SAA), are compared to the GA and the SAA. Computational results show that the proposed HSIM-META has suitable accuracy and speed for use in real world applications.



## 1. Introduction

A Supply Chain Network (SCN) is a dynamic system that includes all activities involved in the life cycle of products, from processing the raw material until delivery to customers. These activities include manufacturing, inventory control systems, distribution channels, warehousing, customer services etc. [1]. The SCN has been widely investigated for its competitive advantages in today's business world. A SCN consists of some suppliers, manufacturing plants, Distribution Centers (DCs), and customers. The impact of competition forces suppliers, manufacturers, and DCs to collaborate efficiently with each other on the entire SCN. The concept of the SCN is presented in Figure 1 [2]. Supply Chain Management (SCM) coordinates and integrates all these activities into a smooth process. The main objective of a SCM system is to minimize system-wide costs while satisfying service-level requirements with increasing global competition, even in emergence of e-business deals. SCM is viewed as a major solution for cost reduction and profitability strategies [3].

Recent studies have focused on multi-facility, multi product, and multi-period problems. Several algorithms have been developed to solve SCN problems. Many mathematical programming methods, such as Linear Programming (LP), Integer Programming (IP), and Mixed-Integer Programming (MIP), have been utilized to solve the small-scale problems. On the other

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**Figure 1.** The concept of the supply chain network.

hand, metaheuristic algorithms, such as Genetic Algorithms (GA), Neural Networks (NN), and Simulated Annealing Algorithms (SAA), have been developed to solve large-scale problems, known due to the NP-hardness of a SCN. Real SCN problems have several stochastic parameters, such as demand rate and lead time. Therefore, the simulation approach can be more practical for addressing such a stochastic large-scale real world problem. Chan [4] identified seven categories of quantitative and qualitative performance measurement. These include cost and resource utilization as quantitative, and quality, flexibility, visibility, trust, and innovativeness as qualitative.

Also, several studies proposed the simulation approach to solve the problem. The simulation approach proposed by Lee et al. [5] was based on the equation of continuous portion in the SCN architecture in modelling the problem. The architecture includes and describes how these portions can be used in SCN simulation models. Joines et al. [6] utilized a SCN simulation, optimization methodology, using GA to optimize system parameters. Jang et al. [7] and Lim et al. [8] introduced a Bill Of Material (BOM) relationship between manufacturing plants. Long and Lin [9] proposed a framework of a multi-agent-based distributed simulation platform for SCN. Pan et al. [10] provided a systematic approach for analyzing and designing SCN construction. They utilized a simulation technique to explore the behaviour of the SCN and find the near optimal solutions. Akgul et al. [11] commented on optimization-based methods for biofuel supply chain assessment under uncertainty. The work identifies mathematical programming, as well as simulation-based methods, as being relevant to this field. Weare and Fagerholt [12] studied optimal planning of offshore SCN. Considering major uncertainty elements, such as weather impact, on sailing and loading operations, they described how voyage-based solution methods can be used to provide decision support in the supply vessel planning process. In their proposed solution, the simulation was combined with an optimization method to create a more robust fleet, and schedule solutions for supply planning. Some modelling techniques to model SCN under uncertainty were presented by Awudu and Zhang [13]. Their work focused on biorefinery SCN, while researchers made the point that there is limited literature regarding uncertainty, specifically in the biorefinery SCN context. They concluded that all supply chains are under uncertainty conditions. The researchers used analytical methods and simulation-based techniques. Zengin et al. [14] investigated discrete event simulation with its robust, accurate modelling, and analysis capabilities. Long and Zhang [15] proposed an integrated framework for agent-based inventory production-transportation modelling and distributed simulation of SCN. This extended framework provides users with a meta-agent class library and a multi-agent-based distributed platform for SCN to build an agent-based simulation model visually and rapidly using meta-agents as building blocks. Further, it supports the independent building of sub-simulation models, implementing and synchronizing them together in a distributed environment.

Research that has utilized metaheuristic algorithms can be investigated as follows. Chan et al. [16] developed a hybrid GA for production-distribution problems in multi-factory SCN models, and solved a hypothetical production-distribution problem using this algorithm. Chan and Chung [17] presented an optimization algorithm to solve the problem of demand allocation, transportation, and production scheduling in a demand-driven multi-echelon distribution network, especially considering demand due date. The proposed optimization algorithm was combined with GA and the Analytic Hierarchy Process (AHP). Gen and Syarif [18] proposed a new technique, called a spanning tree-based GA, for solving production-distribution problems. They integrated production, distribution, and inventory systems, so that products were produced and distributed in the right quantities, to the right customers, and at the right times. The goal was to minimize total costs while satisfying all customer demands. Syami [19] studied the traditional facility location problem considering logistic costs. To this end, two different heuristics, based on Lagrange relaxation and SAA, were used. Ross [20] proposed a two-phase approach for a SCN. The first phase includes a strategy that selects the best set of distribution centers to be opened, and the second is an operational decision that includes customer and resource assignments. The SAA is applied to solve this problem. Jayaraman and Ross [21] provided a distribution network in two models, focusing on two key stages: planning and implementing. Determining warehouse and cross-dock center allocation to open warehouses, and family product allocation from warehouse to cross-dock center are all results of solving the first model. The second model is an operational model aiming to minimize the cost of transportation to warehouses, the cost of transportation from warehouses to cross-dock centers and the cost of product distribution to the customers. SAA is used to achieve near optimal solutions for both models. Zhang et al. [22] presented an extended GA to support the multi-objective decision-making optimization for the SCN. They showed that their proposed approach can obtain the optimal manufacturing resource allocation plan within a reasonable time in the proposed case studies. Xian-cheng et al. [23] proposed a genetic-particle swarm optimization algorithm for closed-loop SCN. They show that their algorithm provides a new way to design closed-loop SCN and gain good convergent performance and rapidity. Furlan et al. [24], Sukumara et al. [25], and Caballero et al. [26] combined process simulation and optimization to optimize the combinatorial optimization problems.

In this research, the mathematical model from Lim et al. [8] was developed by considering capacitated warehouses and defining some new relevant variables to the basic model for each echelon to make the SCN model much more realistic. For example, in some industrial companies, such as iron melting industries, many products have particular length and width sizes, and, thus, keeping them in un-capacitated warehouses for long times is impossible. Therefore, the warehouse capacities of these companies are limited. According to Lim et al. [8] this problem is an NP-hard problem, so, two hybrid simulation-metaheuristic algorithms, called HSIM-META, were developed to solve the SCN model. The simulation is used to solve and fix the routes of the SCN and computing of the total costs. Then, these feasible solutions are used as the initial population in metaheuristic algorithms to find near optimum solutions. To the best of our knowledge, there is no similar approach in dealing with the SCN, which combines simulation and metaheuristic algorithms to solve the model. However, using simulation, or combining simulation with metaheuristics (OVS), is not a new approach in SCN literature, but this is the first time that a new OVS method has been developed for the SCN. Usually, in OVS methods, the simulation replications are used to calculate the fitness function. Sometimes the simulation replications are used to produce a regression model to be used as the fitness function. Sometimes, at each iteration of the metaheuristic, whenever the algorithm wants to calculate the fitness function, it replicates the simulation model to achieve this value. This novel approach connects the simulation model and the metaheuristics through construction of the initial population. Based on conjecture, wherein having an initial good feasible population, instead of random initial ones, can terminate the metaheuristics faster, the simulation model helps to produce several feasible solutions randomly in a very short time (1000 solutions in less than 1 second). This conjecture has been proved at least for the current problem, i.e. the initial high quality population can result in a faster termination. The optimum solution may be among these generated solutions, or, at least, the best solution could be a good lower bound for the main problem. This capability helps metaheuristics to start from a good basis and to reject many non-promising solutions.

This paper is organized in the following way. In Section 2, the mathematical model is presented. In Section 3, the solution methodologies are explained by introducing GA and SAA. Then, the proposed hybrid simulation-metaheuristics (HSIM-META) are especially described with their components. The link between simulation results and metaheuristics is also presented by developing and testing three different scenarios. The best one has been selected based on minimizing total costs, including fixed set up costs, production costs, inventory holding costs, and transportation costs. In Section 4, the computational results have been presented which compare the results of HSIM-META with normal GA and SAA. Finally, concluding remarks and suggestions for future research are presented in Section 5.

## 2. Mathematical model

The SCN model in this study has five echelons, including suppliers, sub assembly factories, final assembly factories, DCs, and final customers. The cost parameters assumed in the model are production, transportation, inventory holding, and facility set up costs. An example case of a SCN used for this study is presented in Figure 2.

The assumed SCN procures raw material from the suppliers and processes them into the sub-assembled products in sub-assembly factories. These sub-assembled products are then transported to the final assembly factories for producing the assembled products, and, then, final assembly products are transported to the distribution centers to fulfill customer demand.

The basic formulation of the SCN problem was taken from Lim et al. [8] with some revisions, including the warehouse capacities for all factories at each echelon, and by adding some relevant variables to the basic model.

The following assumptions are made regarding the underlying SCN at each period of time:

- Suppliers, manufacturing plants, DCs, customers, and products are known;
- The customer demands of each product are known and confident;
- The locations of the suppliers, manufacturing plants, DCs, and customers are known;
- The set up time are assumed to be negligible;
- All cost parameters are known and confident;
- All manufacturing plants and DCs have relevant capacity for production and inventory;

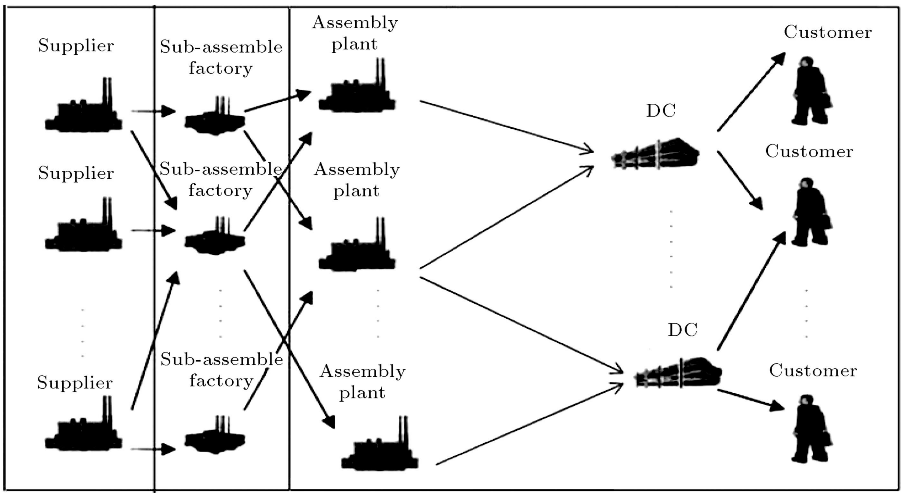


**Figure 2.** An example of the supply chain network for this study.

- The bill of material (BOM) of each sub product of any final product is known, and the consumption ratio is 1:1.

The following notations are used:

**Indices**

| | |
|---|---|
| $c$ | Index of raw materials ($c = 1, 2, ..., C$); |
| $v$ | Index of sub-assembled products ($v = 1, 2, ..., V$); |
| $K$ | Index of final assembled products ($k = 1, 2, ..., K$); |
| $e$ | Index of suppliers ($e = 1, 2, ..., E$); |
| $s$ | Index of sub-assembly factories ($s = 1, 2, ..., S$); |
| $P$ | Index of final assembly factories ($p = 1, 2, ..., P$); |
| $J$ | Index of distribution centers ($j = 1, 2, ..., J$); |
| $d$ | Index of customers ($d = 1, 2, ..., D$); |
| $T$ | Index of time periods ($t = 1, 2, ..., T$). |

**Parameters**

| | |
|---|---|
| $P_{cet}$ | Fixed set up cost of $e$ for $c$ at time period $t$; |
| $P_{vst}$ | Fixed set up cost of $s$ for $v$ at time period $t$; |
| $P_{kpt}$ | Fixed set up cost of $p$ for $k$ at time period $t$; |
| $P_{kjt}$ | Fixed set up cost of $j$ for $k$ at time period $t$; |
| $C_{ces}$ | Unit production cost of $c$ at $e$ to $s$ at time period $t$; |
| $C_{vspt}$ | Unit production cost of $v$ at $s$ to $p$ at time period $t$; |
| $C_{kpjt}$ | Unit production cost of $k$ at $p$ to $j$ at time period $t$; |
| $HC_{cet}$ | Unit inventory holding cost of $c$ at $e$ at time period $t$; |
| $HC_{csvt}$ | Unit inventory holding cost of $c$ at $s$ to $v$ at time period $t$; |
| $HC_{vst}$ | Unit inventory holding cost of $v$ at $s$ at time period $t$; |
| $HC_{vpkt}$ | Unit inventory holding cost of $v$ at $p$ to $k$ at time period $t$; |
| $HC_{kpt}$ | Unit inventory holding cost of $k$ at $p$ at time period $t$; |
| $HC_{kjt}$ | Unit inventory holding cost of $k$ at $j$ at time period $t$; |
| $TC_{cest}$ | Unit transporting cost of $c$ from $e$ to $s$ at time period $t$; |
| $TC_{vspt}$ | Unit transporting cost of $v$ from $s$ to $p$ at time period $t$; |
| $TC_{kpjt}$ | Unit transporting cost of $k$ from $p$ to $j$ at time period $t$; |
| $TC_{kjdt}$ | Unit transporting cost of $k$ from $j$ to $d$ at time period $t$; |
| $A_{dkt}$ | Demand of $k$ for $d$ at time period $t$; |
| $TN_{ce}$ | Processing time of $c$ at $e$; |
| $TN_{vs}$ | Processing time of $v$ at $s$; |
| $TN_{kp}$ | Processing time of $k$ at $p$; |
| $Q_{cet}$ | Total available production capacity of $c$ at $e$ at time period $t$; |
| $Q_{vst}$ | Total available production capacity of $v$ at $s$ at time period $t$; |
| $Q_{kpt}$ | Total available production capacity of $k$ at $p$ at time period $t$; |
| $R_{cet}$ | Total available inventory capacity of $c$ at $e$ at time period $t$; |
| $R_{cst}$ | Total available inventory capacity of $c$ at $s$ at time period $t$; |

$R_{vst}$ Total available inventory capacity of $v$ at $s$ at time period $t$;

$R_{vpt}$ Total available inventory capacity of $v$ at $p$ at time period $t$;

$R_{kpt}$ Total available inventory capacity of $k$ at $p$ at time period $t$;

$R_{kjt}$ Total available inventory capacity of $k$ at $j$ at time period $t$;

$M$ A large positive integer number.

**Variables**

$X_{cest}$ Production amount of $c$ at $e$ to $s$ at the end of period $t$;

$X_{vspt}$ Production amount of $c$ at $e$ to $s$ at the end of period $t$;

$X_{kpjt}$ Production amount of $k$ at $p$ to $j$ at the end of period $t$;

$I_{cet}$ Inventory amount of $c$ at $e$ at the end of period $t$;

$I_{csvt}$ Inventory amount of $c$ at $s$ to $v$ at the end of period $t$;

$I_{vst}$ Inventory amount of $v$ at $s$ at the end of period $t$;

$I_{vpkt}$ Inventory amount of $v$ at $p$ to $k$ at the end of period $t$;

$I_{kpt}$ Inventory amount of $k$ at $p$ at the end of period $t$;

$I_{kjt}$ Inventory amount of $k$ at $j$ at the end of period $t$;

$TR_{cest}$ Transportation amount of $c$ from $e$ to $s$ at the end of period $t$;

$TR_{vspt}$ Transportation amount of $v$ from $s$ to $p$ at the end of period $t$;

$TR_{kpjt}$ Transportation amount of $k$ from $p$ to $j$ at the end of period $t$;

$TR_{kjdt}$ Transportation amount of $k$ from $j$ to $d$ at the end of period $t$.

$$W_{cest}\begin{cases}1, & \text{if transportation takes place from } e \text{ to } s \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

$$W_{vspt}\begin{cases}1, & \text{if transportation takes place from } s \text{ to } p \text{ of } v \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

$$W_{kpjt}\begin{cases}1, & \text{if transportation takes place from } p \text{ to } j \text{ of } k \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

$$W_{kjdt}\begin{cases}1, & \text{if transportation takes place from } j \text{ to } d \text{ of } k \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

$$U_{cet}\begin{cases}1, & \text{if production takes place for } c \text{ at supplier } e \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

$$U_{vst}\begin{cases}1, & \text{if production takes place for } v \text{ at the final assembly factory } s \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

$$U_{kpt}\begin{cases}1, & \text{if production takes place for } k \text{ at the final assembly factory } p \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

$$U_{kjt}\begin{cases}1, & \text{if DC } j \text{ is opened for } k \text{ at the end of period } t\\ 0, & \text{otherwise}\end{cases}$$

The mathematical model (Problem 1) is presented as follows:

Minimize

$$\sum_c\sum_e\sum_t\Big((P_{cet}U_{cet})+(HC_{cet}I_{cet})+\sum_s(C_{cest}X_{cest})\Big)+\sum_v\sum_s\sum_t\Big((P_{vst}U_{vst})+(HC_{vst}I_{vst})+\sum_p(C_{vspt}X_{vspt})\Big)$$
$$+\sum_k\sum_p\sum_t\Big((P_{kpt}U_{kpt})+(HC_{kpt}I_{kpt})+\sum_j(C_{kpjt}X_{kpjt})\Big)+\sum_c\sum_s\sum_v\sum_t(HC_{csvt}I_{csvt})$$
$$+\sum_v\sum_p\sum_k\sum_t(HC_{vpkt}I_{vpkt})$$
$$+\sum_k\sum_j\sum_t\Big((P_{kjt}U_{kjt})+(HC_{kjt}I_{kjt})\Big)$$

$$+\sum_c\sum_e\sum_s\sum_t(TC_{cest}TR_{cest})$$

$$+\sum_v\sum_s\sum_p\sum_t(TC_{vspt}TR_{vspt})$$

$$+\sum_k\sum_p\sum_j\sum_t(TC_{kpjt}TR_{kpjt})$$

$$+\sum_k\sum_j\sum_d\sum_t(TC_{kjdt}TR_{kjdt}) \qquad (1)$$

St:

$$\sum_s(TN_{ce}X_{cest}) \leq Q_{cet}U_{cet}, \qquad \forall c,e,t, \qquad (2)$$

$$\sum_p(TN_{vs}X_{vspt}) \leq Q_{vst}U_{vst}, \qquad \forall v,s,t, \qquad (3)$$

$$\sum_j(TN_{kp}X_{kpjt}) \leq Q_{kpt}U_{kpt}, \qquad \forall k,p,t, \qquad (4)$$

$$I_{cet} \leq R_{cet}U_{cet}, \qquad \forall c,e,t, \qquad (5)$$

$$I_{csvt} \leq R_{cst}U_{vst}, \qquad \forall c,s,v,t, \qquad (6)$$

$$I_{vst} \leq R_{vst}U_{vst}, \qquad \forall v,s,t, \qquad (7)$$

$$I_{vpkt} \leq R_{vpt}U_{kpt}, \qquad \forall v,p,k,t, \qquad (8)$$

$$I_{kpt} \leq R_{kpt}U_{kpt}, \qquad \forall k,p,t, \qquad (9)$$

$$I_{kjt} \leq R_{kjt}U_{kjt}, \qquad \forall k,j,t, \qquad (10)$$

$$X_{cest} \leq MU_{cet}, \qquad \forall c,e,s,t, \qquad (11)$$

$$X_{vspt} \leq MU_{vst}, \qquad \forall c,e,s,t, \qquad (12)$$

$$X_{kpjt} \leq MU_{kpt}, \qquad \forall c,e,s,t, \qquad (13)$$

$$TR_{cest} \leq MW_{cest}, \qquad \forall c,e,s,t, \qquad (14)$$

$$TR_{vspt} \leq MW_{vspt}, \qquad \forall v,s,p,t, \qquad (15)$$

$$TR_{kpjt} \leq MW_{kpjt}, \qquad \forall k,p,j,t, \qquad (16)$$

$$TR_{kjdt} \leq MW_{kjdt}, \qquad \forall k,j,d,t, \qquad (17)$$

$$\sum_s X_{cest}+I_{cet}-\sum_s TR_{cest}-I_{cet-1}=0, \quad \forall c,e,t, \qquad (18)$$

$$\sum_p X_{vspt}+I_{vst}-\sum_p TR_{vspt}-I_{vst-1}=0, \quad \forall v,s,t, \qquad (19)$$

$$\sum_j X_{kpjt}+I_{kpt}-\sum_j TR_{kpjt}-I_{kpt-1}=0, \quad \forall k,p,t, \qquad (20)$$

$$I_{kjt-1}-I_{kjt}-TR_{kjdt}+A_{dkt}=0, \quad \forall k,j,d,t, \qquad (21)$$

$$\sum_p X_{vspt} \geq \sum_c\sum_e X_{cest}-\sum_c I_{csvt-1}, \quad \forall v,s,t, \qquad (22)$$

$$\sum_j X_{kpjt} \geq \sum_v\sum_s X_{vspt}-\sum_v I_{vpkt-1}, \quad \forall k,p,t, \qquad (23)$$

$$X_{cest}, X_{vspt}, X_{kpjt} \geq 0 \quad \forall c,e,s,v,p,k,j,t, \qquad (24)$$

$$I_{cmt}, I_{csvt}, I_{vst}, I_{vpkt}, I_{kpt}, I_{kjt} \geq 0 \quad \forall c,m,s,v,p,k,j,t, \qquad (25)$$

$$TR_{cmst}, TR_{vspt}, TR_{kpjt}, TR_{kjdt} \geq 0 \quad \forall c,m,s,v,p,k,j,d,t, \qquad (26)$$

$$U_{cet}, U_{vst}, U_{kpt}, U_{kjt}, W_{cest}, W_{vspt}, W_{kpjt}, W_{kjdt} \in \{0,1\} \qquad (27)$$

The objective function of this model is to minimize the total costs, including set up, production, inventory holding, and transportation costs through the model. Constraints (2)-(4) represent the capacity restrictions for each supplier, sub-assembly factory, and final assembly factory. Constraints (5)-(10) represent the capacity restriction for the supplier, warehouse, sub-assembly warehouse, final assembly warehouse, and DC. Constraints (11)-(13) ensure that a set up event occurs when a factory manufactures an item such as raw material, sub-assembled product, or final-assembled product. Constraints (14)-(17) imply that a link among plants exists if the transportation quantities are non-zero. Constraints (18)-(21) represent a balance equation that defines the inventory levels for items $c$, $v$, and $k$ at the end of period $t$ at each plant, and DC results from production and transportation procedures. Constraints (22) and (23) ensure that the external demands must be satisfied. Constraints (24)-(26) represent the non-negativity restrictions on the decision variables. Constraint (27) shows the integer 0-1 variables. It should be mentioned that Constraint sets (5)-(10) have been added to the basic model of Lim et al. [8] as limited capacity warehouses of factories at each echelon.

## 3. Solution methodologies

At first, general metaheuristic algorithms, including the Genetic Algorithm (GA) and the Simulated Annealing Algorithm (SAA) are briefly described, and, then, the proposed HSIM-GA and HSIM-SAA and their components are especially described.

### 3.1. Genetic algorithm in general

The Genetic Algorithm (GA) is a well-known metaheuristic optimization technique originally developed by Holland [27]. Vose [28] provided the whole concept of the basic GA. R.L. Haupt and S.E. Haupt [29] undertook a brief study, including some of the latest research results on applying GA. Briefly, the GA mechanism is based on a natural selection process that starts with an initial set of random solutions (population). Each individual in the population (chromosome) indicates a solution to the problem. During a generation, the chromosomes are evaluated using a cost function. In order to produce the next generation, two operators are used in GA. The first, called the crossover, merges two chromosomes of a current generation to create offspring, and the other, called, mutation, modifies a chromosome. Then, based on cost function values, some parents and offspring having better values of cost function, form a new generation. In this way, better chromosomes of successive generations have higher probabilities of being selected and the algorithm converges to the best chromosome that expectantly indicates the optimum or near optimal solution to the problem after several generations. In general, GA can find the global optimum solution with a high probability.

### *3.2. Simulated annealing algorithm in general*

SAA is a randomized local search method based on simulation of metal annealing. The procedure was popularized by Krikpatrik et al. [30] and is based on the work carried out by Metropolis et al. [31] (also called the Metropolis algorithm) in statistical mechanics. SAA emulates the physical process of annealing, which attempts to force a system to its lowest energy state through a controlled cooling procedure. In a physical system with a large number of atoms, equilibrium may be characterized as the minimal value for the energy of the system. This is accomplished by a slow cooling of the temperature. Then, the system is said to be at thermal equilibrium at temperature $T$ if the probability of being in state $i$ with energy $E_i$ follows the Bultzen distribution:

$$Prob\{x=i\}=\frac{\exp\left\{\frac{-E_i}{K_BT}\right\}}{\sum\exp\{\frac{-E_i}{K_BT}\}}, \tag{28}$$

where $K_B$ is the Bultzen constant and the sum extends to all possible states. By moving the atoms randomly to new configurations, different energy changes are induced ($\Delta E$). If the increment is negative, the new configuration is accepted as a new state, but if the configuration has higher energy than the previous state, it is only accepted with a certain probability, as follows:

$$\exp\left\{\frac{-\Delta E}{K_BT}\right\}. \tag{29}$$

By repeating these steps, it is shown that the accepted configurations converge to the Bultzen distribution after some indeterminate number of iterations at each particular temperature. The procedure may be easily applied to a large number of optimization problems, where the objective function plays the role of energy. In this context, the temperature is a control parameter to define large or small moves for the optimization variables.

### *3.3. Proposed hybrid simulation-metaheuristics algorithm (HSIM-META)*

As mentioned earlier, Problem 1 is an NP-hard problem and, so, metaheuristic algorithms can be potentially appropriate for solving the problem. On the other hand, the SCN has several stochastic parameters which cannot be dealt with via mathematical programming approaches, especially in large scale problems. Therefore, the simulation is used to model the real world SCN problems. First, a mathematical model is constructed similar to Problem 1 and, then, this model is used to construct the corresponding simulation model. All constraints in Problem 1 are coded in the simulation software in such a way that each run results in a feasible solution. Then, the simulation model is run and the best production-distribution routes for each customer are obtained. Also, each run is terminated when all demands of customers are satisfied. Next, the output solutions of simulation are used as the initial population in the proposed tuned metaheuristics. The metaheuristics run and its circle is repeated until the stopping criteria are satisfied. Therefore, the simulation model has two key specifications in the tuned parameter proposed HSIM-META algorithm. First, it produces some feasible solutions which can be used in the GA and SAA as initial population, and, second, it covers and handles the stochastic behaviour of the SCN. In the next subsection, we describe the essential components of the HSIM-GA and HSIM-SAA in detail.

#### *3.3.1. The chromosome representation of HSIM-GA*

The first important step in utilizing the proposed HSIM-GA algorithm is the chromosome representation. We design a heuristic chromosome, which can generate feasible solutions and which satisfies the majority of constraints (Constraint sets (2)-(17)). Our chromosome structure is a $N^*T$ super matrix, where, $N$ is the number of the submatrix, which illustrates suppliers, sub-assembly factories, final assembly factories, DCs and customers, and $T$ is the period of time. An example of the chromosome structure is shown in Figure 3. In this figure, we describe submatrix numbers 1, 2, 3, and 10 as an example.

The main important questions related to the production, warehousing, and transportation capacities of the SCN at each echelon are as follows:

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|
| Production amount of raw materials | Inventory amounts of raw materials in suppliers | Transportation amount of raw materials from suppliers to sub-assembly factories | Production amount of sub-assembled products | Inventory amounts of sub-assembled products in sub-assembly factories | Transportation amount of raw materials from suppliers to sub-assembly factories | Production amount of final assembled products | --- | Transportation amount of final assembled products from DC's to customers |

| 1 | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 |
|---|---|---|---|---|
| Supplier 1 | $X_{11}$ | $X_{12}$ | $X_{13}$ | $X_{14}$ |
| Supplier 2 | $X_{21}$ | $X_{22}$ | $X_{23}$ | $X_{24}$ |
| Supplier 3 | $X_{31}$ | $X_{32}$ | $X_{33}$ | $X_{34}$ |
| Supplier 4 | $X_{41}$ | $X_{42}$ | $X_{43}$ | $X_{44}$ |
| Supplier 5 | $X_{51}$ | $X_{52}$ | $X_{53}$ | $X_{54}$ |

| 2 | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 |
|---|---|---|---|---|
| Supplier 1 | $I_{11}$ | $I_{12}$ | $I_{13}$ | $I_{14}$ |
| Supplier 2 | $I_{21}$ | $I_{22}$ | $I_{23}$ | $I_{24}$ |
| Supplier 3 | $I_{31}$ | $I_{32}$ | $I_{33}$ | $I_{34}$ |
| Supplier 4 | $I_{41}$ | $I_{42}$ | $I_{43}$ | $I_{44}$ |
| Supplier 5 | $I_{51}$ | $I_{52}$ | $I_{53}$ | $I_{54}$ |

| 3 | Sub factory 1 | Sub factory 2 | Sub factory 3 | Sub factory 4 |
|---|---|---|---|---|
| Supplier 1 | $TR_{11}$ | $TR_{12}$ | $TR_{13}$ | $TR_{14}$ |
| Supplier 2 | $TR_{21}$ | $TR_{22}$ | $TR_{23}$ | $TR_{24}$ |
| Supplier 3 | $TR_{31}$ | $TR_{32}$ | $TR_{33}$ | $TR_{34}$ |
| Supplier 4 | $TR_{41}$ | $TR_{42}$ | $TR_{43}$ | $TR_{44}$ |
| Supplier 5 | $TR_{51}$ | $TR_{52}$ | $TR_{53}$ | $TR_{54}$ |

| 10 | Customer 1 | Customer 2 | Customer 3 | Customer 4 |
|---|---|---|---|---|
| DC 1 | $TR_{11}$ | $TR_{12}$ | $TR_{13}$ | $TR_{14}$ |
| DC 2 | $TR_{21}$ | $TR_{22}$ | $TR_{23}$ | $TR_{24}$ |
| DC 3 | $TR_{31}$ | $TR_{32}$ | $TR_{33}$ | $TR_{34}$ |
| DC 4 | $TR_{41}$ | $TR_{42}$ | $TR_{43}$ | $TR_{44}$ |

**Figure 3.** An example of the chromosome structure.

I. How many products should be produced at each factory?

II. How many products should be transported to the next echelon?

To answer these questions, we introduce a heuristic method for randomly generating a feasible initial population which can consider these constraints. The following example presents the proposed heuristic:

$$X_1 + X_2 + X_3 + X_4 + X_5 = 2000, \tag{30}$$

$$X_1 \leq 1100, \tag{31}$$

$$X_2 \leq 500, \tag{32}$$

$$X_3 \leq 400, \tag{33}$$

$$X_4 \leq 300, \tag{34}$$

$$X_5 \leq 100. \tag{35}$$

Suppose that the above model represents the first row of submatrix 1, including the production amount of raw material, type 1, at the suppliers. Constraint (30) shows that the total amount of raw material produced by the suppliers is equal to 2000. Also, Constraint sets (31)-(35) implies that the maximum production capacity of suppliers 1, 2, 3, 4 and 5 to produce raw material type 1 are 1100, 500, 400, 300 and 100, respectively. According to the above information, we can infer that suppliers 2, 3, 4, and 5 can produce, totally, 1300 units of raw material type 1 if they work with maximum capacity. Also, we can conclude that supplier 1 should, at least, produce 700 units of raw material, type 1, to satisfy Constraint (30). Therefore, if suppliers 3, 4, and 5 work with maximum capacity, they can produce 800 units of raw material type 1, totally, and supplier 2 should at least produce 200 units of raw material, type 1. Also, suppliers 4 and 5 can produce totally 400 units of raw material, type 1, if they work at maximum capacity. Therefore, supplier 3 should at least produce 200 units of raw material, type 1, to satisfy Constraint (30). Next, we can conclude that supplier 4 should at least produce 200 units of raw material, type 1, to satisfy Constraint (30). According to the information, we could fill submatrix 1 as follows:

$$X_1 = \text{Uniform } (700, 1100) = 1000, \tag{36}$$

$$X_2 \leq 500, \tag{37}$$

$$X_3 \leq 400, \tag{38}$$

$$X_4 \leq 300, \tag{39}$$

$$X_5 \leq 100, \tag{40}$$

$$X_2 + X_3 + X_4 + X_5 = 1000, \tag{41}$$

$$X_2 = \text{Uniform } (200, 500) = 400, \tag{42}$$

$$X_3 + X_4 + X_5 = 600, \tag{43}$$

$$X_3 = \text{Uniform } (200, 400) = 300, \tag{44}$$

$$X_4 + X_5 = 300, \tag{45}$$

$$X_4 = \text{Uniform } (200, 300) = 250, \tag{46}$$

$$X_5 = 2000 - 1000 - 400 - 300 - 250 = 50. \tag{47}$$

A graphical representation of the described heuristic method can be found in Figure 4(a)-(e), in which all manufacturing plants, such as suppliers, sub-assembly factories, and final assembly factories, produce according to the their production capacity constraints (this procedure is utilized for Constraint sets (2)-(17).

#### *3.3.2. Initialization of HSIM-GA*

The input parameters of our HSIM-GA is the population size ($N_{Pop}$), which shows the total number of chromosomes in each generation, crossover probability ($P_c$) and mutation probability ($P_m$).

#### *3.3.3. The cross over operator of HSIM-GA*

The goal of cross over is to explore new solution space. The cross over operator corresponds to exchanging the parts of the strings of selected parents. In general, there

$$\begin{cases} X_{11}+X_{12}+X_{13}+X_{14}+X_{15} \le 1000 \\ X_{21}+X_{22}+X_{23}+X_{24}+X_{25} \le 400 \\ X_{31}+X_{32}+X_{33}+X_{34}+X_{35} \le 300 \\ X_{41}+X_{42}+X_{43}+X_{44}+X_{45} \le 250 \\ X_{51}+X_{52}+X_{53}+X_{54}+X_{55} \le 50 \\ X_{11}+X_{21}+X_{31}+X_{41}+X_{51} \le 800 \\ X_{12}+X_{22}+X_{32}+X_{42}+X_{52} \le 650 \\ X_{13}+X_{23}+X_{33}+X_{43}+X_{53} \le 300 \\ X_{14}+X_{24}+X_{34}+X_{44}+X_{54} \le 250 \end{cases} \rightarrow$$

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | $X_{11}$ | $X_{12}$ | $X_{13}$ | $X_{14}$ | **1000** |
| Supplier 2 | $X_{21}$ | $X_{22}$ | $X_{23}$ | $X_{24}$ | **400** |
| Supplier 3 | $X_{31}$ | $X_{32}$ | $X_{33}$ | $X_{34}$ | **300** |
| Supplier 4 | $X_{41}$ | $X_{42}$ | $X_{43}$ | $X_{44}$ | **250** |
| Supplier 5 | $X_{51}$ | $X_{52}$ | $X_{53}$ | $X_{54}$ | **50** |
| Total production | **800** | **600** | **300** | **250** | **2000** |

(a)

$$\begin{cases} X_{11} = \text{Uniform } (1, 1000) = 420 \\ X_{21} = \text{Uniform } (1, 400) = 170 \\ X_{31} = \text{Uniform } (1, 300) = 80 \\ X_{41} = \text{Uniform } (1, 250) = 120 \\ X_{51} = \text{Uniform } (1, 50) = 10 \end{cases} \rightarrow$$

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 420 | $X_{12}$ | $X_{13}$ | $X_{14}$ | **580** |
| Supplier 2 | 170 | $X_{22}$ | $X_{23}$ | $X_{24}$ | **230** |
| Supplier 3 | 80 | $X_{32}$ | $X_{33}$ | $X_{34}$ | **220** |
| Supplier 4 | 120 | $X_{42}$ | $X_{43}$ | $X_{44}$ | **130** |
| Supplier 5 | 10 | $X_{52}$ | $X_{53}$ | $X_{54}$ | **40** |
| Total production | **800** | **600** | **300** | **250** | |

(b)

$$\begin{cases} X_{12} = \text{Uniform } (1, 580) = 380 \\ X_{22} = \text{Uniform } (1, 230) = 100 \\ X_{32} = \text{Uniform } (1, 220) = 80 \\ X_{42} = \text{Uniform } (1, 130) = 70 \\ X_{52} = \text{Uniform } (1, 40) = 20 \end{cases} \rightarrow$$

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 420 | 380 | $X_{13}$ | $X_{14}$ | **200** |
| Supplier 2 | 170 | 100 | $X_{23}$ | $X_{24}$ | **130** |
| Supplier 3 | 80 | 80 | $X_{33}$ | $X_{34}$ | **140** |
| Supplier 4 | 120 | 70 | $X_{43}$ | $X_{44}$ | **60** |
| Supplier 5 | 10 | 20 | $X_{53}$ | $X_{54}$ | **20** |
| Total production | **800** | **650** | **300** | **250** | |

(c)

$$\begin{cases} X_{13} = \text{Uniform } (1, 200) = 140 \\ X_{23} = \text{Uniform } (1, 130) = 70 \\ X_{33} = \text{Uniform } (1, 140) = 50 \\ X_{43} = \text{Uniform } (1, 60) = 30 \\ X_{53} = \text{Uniform } (1, 20) = 10 \end{cases} \rightarrow$$

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 420 | 380 | 140 | $X_{14}$ | **60** |
| Supplier 2 | 170 | 100 | 70 | $X_{24}$ | **60** |
| Supplier 3 | 80 | 80 | 50 | $X_{34}$ | **90** |
| Supplier 4 | 120 | 70 | 30 | $X_{44}$ | **30** |
| Supplier 5 | 10 | 20 | 10 | $X_{54}$ | **10** |
| Total production | **800** | **650** | **300** | **250** | |

(d)

$$\begin{cases} X_{14} = 1000 - 420 - 380 - 140 = 60 \\ X_{24} = 400 - 170 - 100 - 70 = 60 \\ X_{34} = 300 - 80 - 80 - 50 = 90 \\ X_{44} = 250 - 120 - 70 - 30 = 30 \\ X_{54} = 50 - 10 - 20 - 10 = 10 \end{cases} \rightarrow$$

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 420 | 380 | 140 | 60 | **1000** |
| Supplier 2 | 170 | 100 | 70 | 60 | **400** |
| Supplier 3 | 80 | 80 | 50 | 90 | **300** |
| Supplier 4 | 120 | 70 | 30 | 30 | **250** |
| Supplier 5 | 10 | 20 | 10 | 10 | **50** |
| Total production | **800** | **650** | **300** | **250** | **2000** |

(e)

**Figure 4.** An example of the chromosome filling structure.

are three ways to keep the initial solutions feasible by cross over, as follows:

- Assume penalty functions for infeasible solutions;
- Return the infeasible solutions to feasible solutions by special techniques;
- Keep every new generated solution feasible.

After generating feasible submatrixes as parents, the proposed cross over operator is used as follows:

1. Two chromosomes are selected according to the roulette wheel selection method;
2. Every cell of parent 1 is added to the corresponding cell of parent 2, then, this value is divided by two. In other words, the average of the two parents is called the offspring. These calculations are repeated for all submatrixes at each period of time.

This cross over operator ensures that all generated offsprings are feasible and one never comes out of the feasible region. An example of the proposed cross over operator of submatrix 1 is illustrated in Figure 5.

*3.3.4. The mutation operator of HSIM-GA*

Mutation is undertaken to prevent premature convergence and to explore new solution space. We introduce a new mutation operator that keeps each generated solution feasible. We consider submatrix 1 to present our mutation operator of HSIM-GA. First, we randomly select a supplier and allocate total productions to it, as follows: One cell of the submatrix is selected and total production is assigned to it. Next, the other submatrix cells are updated considering the total production and capacity of factory constraints. An example of the mutation operator is shown in Figure 6.

At the second step, the essential components of the HSIM-SAA are presented as follows.

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 370 | 400 | 130 | 100 | **1000** |
| Supplier 2 | 195 | 75 | 75 | 55 | **400** |
| Supplier 3 | 90 | 95 | 55 | 60 | **300** |
| Supplier 4 | 130 | 65 | 30 | 25 | **250** |
| Supplier 5 | 15 | 15 | 10 | 10 | **50** |
| Total production | **800** | **650** | **300** | **250** | **2000** |

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 800 | 0 | 100 | 100 | **1000** |
| Supplier 2 | 0 | 240 | 105 | 55 | **400** |
| Supplier 3 | 0 | 185 | 55 | 60 | **300** |
| Supplier 4 | 0 | 195 | 30 | 25 | **250** |
| Supplier 5 | 0 | 30 | 10 | 10 | **50** |
| Total production | **800** | **650** | **300** | **250** | **2000** |

**Figure 6.** An example of the mutation operator.

*3.3.5. Initialization of HSIM-SAA*

The input parameters of the SAA are: Initial temperature ($T_0$), which is the starting temperature point and the temperature decreasing rate ($\alpha$).

*3.3.6. Solution representation of HSIM-SAA*

The solution representation in the HSIM-SAA is similar to the ones described in "The chromosome representation" for HSIM-GA.

*3.3.7. Neighborhood representation of HSIM-SAA*

To present the neighborhood structure, the proposed mutation operator of HSIM-GA, described in "The mutation operator" is utilized to avoid fast convergence of the HSIM-SAA.

*3.3.8. Initial temperature*

A suitable initial temperature is one that results in an average increase of acceptance probability near to one. The value of initial temperature will clearly depend on the scaling of fitness and, hence, it should be problem-specified. Therefore, we first generate a large set of

Parent 1

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 420 | 380 | 140 | 60 | **1000** |
| Supplier 2 | 170 | 100 | 70 | 60 | **400** |
| Supplier 3 | 80 | 80 | 50 | 90 | **300** |
| Supplier 4 | 120 | 70 | 30 | 30 | **250** |
| Supplier 5 | 10 | 20 | 10 | 10 | **50** |
| Total production | **800** | **650** | **300** | **250** | **2000** |

Parent 2

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 320 | 420 | 120 | 140 | **1000** |
| Supplier 2 | 220 | 50 | 80 | 50 | **400** |
| Supplier 3 | 100 | 110 | 60 | 30 | **300** |
| Supplier 4 | 140 | 60 | 30 | 20 | **250** |
| Supplier 5 | 20 | 10 | 10 | 10 | **50** |
| Total production | **800** | **650** | **300** | **250** | **2000** |

Off spring

| | Raw material 1 | Raw material 2 | Raw material 3 | Raw material 4 | Total capacity |
|---|---|---|---|---|---|
| Supplier 1 | 370 | 400 | 130 | 100 | 1000 |
| Supplier 2 | 195 | 75 | 75 | 55 | 400 |
| Supplier 3 | 90 | 95 | 55 | 60 | 300 |
| Supplier 4 | 130 | 65 | 30 | 25 | 250 |
| Supplier 5 | 15 | 15 | 10 | 10 | 50 |

**Figure 5.** An example of cross over operator.

random solutions, then, a standard division of them is calculated and used to determine the initial temperature in such a way that the acceptance probability of primary generations reached 0.95. Consequently, the initial $T$ is set to 1500, based on some preliminary parameter selection examinations, which are described in Subsection 4.1.

*3.3.9. Stopping criteria*

In general, the algorithms could be stopped in the following ways:

- After a predefined number of generations;
- When an individual solution reaches a predefined level of fitness;
- When the variation of individuals from one generation to the next generation reaches a predefined level of stability.

In this paper, the algorithms will be stopped according to the first way, in which, if there is no improvement in the best fitness value for the 50 generations, the algorithms will stop. This stopping criterion is used for both HSIM-GA and HSIM-SAA algorithms. Figures 7 and 8 depict the flowchart of the proposed Hybrid Simulation-Genetic Algorithm (HSIM-GA) and a Hybrid Simulation-Simulated Annealing Algorithm (HSIM-SAA), respectively.

*3.3.10. Allowing infeasibility*

To simplify the escape process from local optimum solutions, the chromosome is allowed to be infeasible, but is penalized according to the amount of infeasibility. An efficient penalty formulation, which is dynamic, is applied in such a way that explores the space in the first and results in infeasible solutions at the end of the evolution. A general form of a distance based penalty method, incorporating a dynamic aspect, is based on the length of the search area for our minimization problem:

$$F_p(x,t) = f(x) + \sum_{s=1}^{s} p_s t, \tag{48}$$

where $p_s$ is a relative scaling for violation of chromosomes from constraint $s$, and $t$ is the generation number. This penalty formulation is capable of visiting highly infeasible solutions at the first steps of the search. By gradually increasing the penalty amount imposed on bad moves, the next solutions tend to be close to the feasible region (this procedure is used for Constraint sets (18)-(23).

## 4. Computational results

All computations were carried out on a PC using a Core i5 with 2.4 GHz CPU, and 4 GB of RAM.

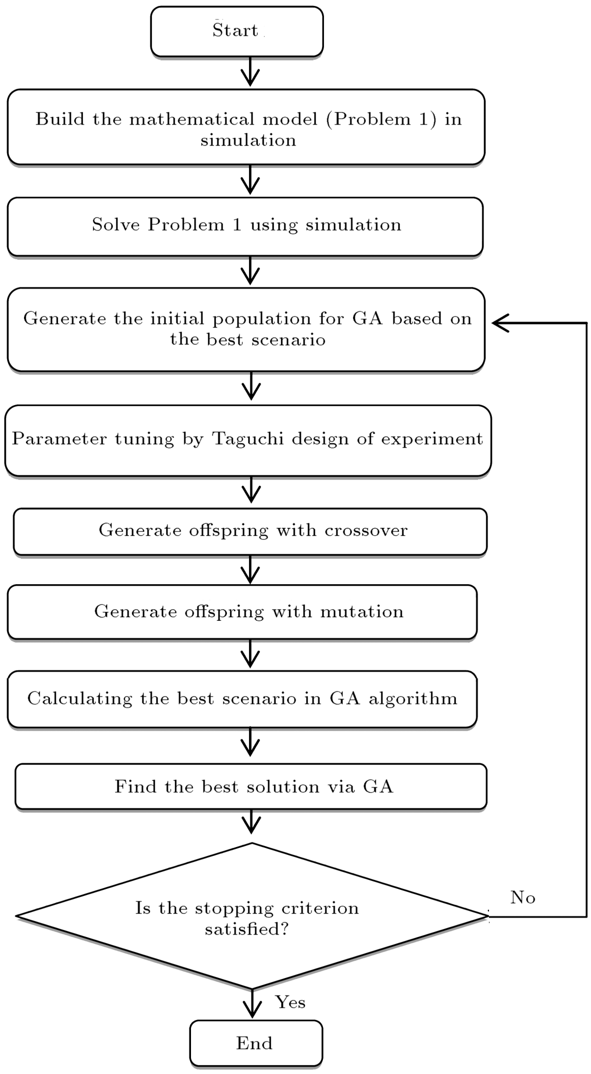


**Figure 7.** The flowchart of the proposed HSIM-GA.

Enterprise Dynamics (ED) 8.2 [32] was used as the simulation software and all constraints in problem 1 were coded in ED 8.2. MATLAB V7.13.0.564, R2011b was used to code the metaheuristics, and the linear programming models have been solved using CPLEX 9.0. Also, Minitab 16 software has been used to tune the parameters. According to Lim et al. [8], the backlogging is not planned in the model and unsatisfied demand in the previous periods is not transferred to the next. The order quantity is computed according to the BOM ratio, which is set to 1 in this study for each echelon. We design a simulation model to impose any excessive costs onto the model, in such a way that when the demand of the last final customer is satisfied, all manufacturing plants at each echelon are stopped. We link the simulation model to the Microsoft Excel so that after each simulation run, the simulation results are exported to the Excel sheets, and the total fixed and variable costs are calculated. Then, the simulation model is replicated and the best production-

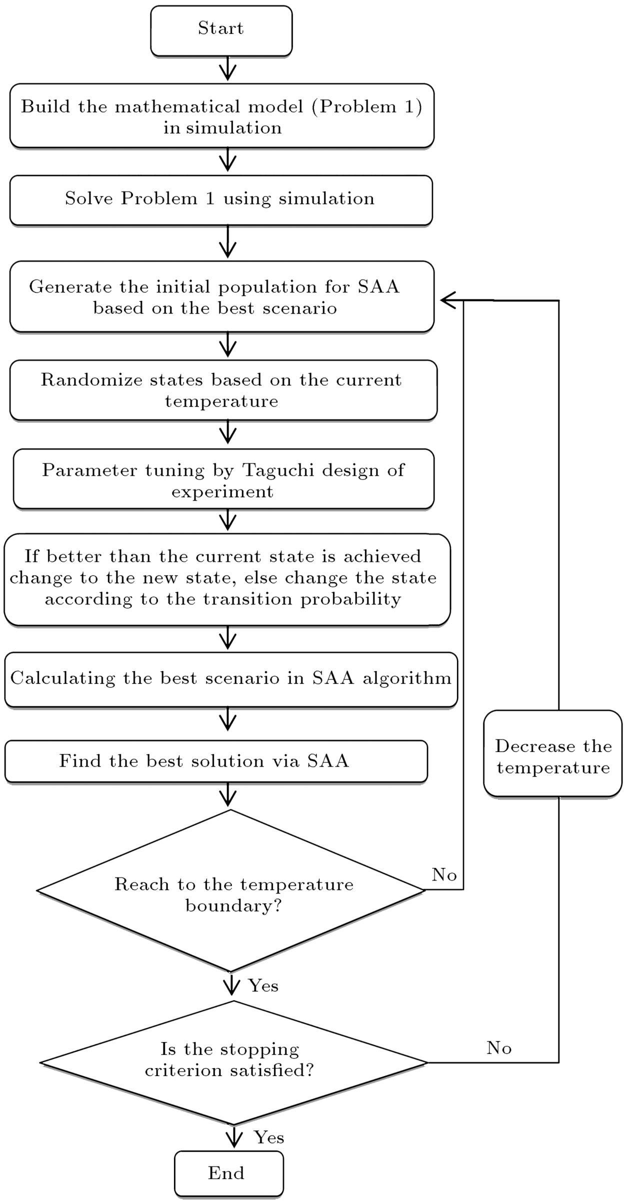


**Figure 8.** The flowchart of the proposed HSIM-SAA.

distribution routes for each customer are obtained. After closing non-economic facilities and warehouses in the simulation model, it is replicated again and total costs are computed. To use the results of the simulation model, each problem is replicated 500 times and the results are saved in Microsoft Excel sheets. Regardless of the volume of goods transported among the different echelons, the simulation model can help to determine the best distribution routes in the SCN. In the second phase, these production-distribution routes are fixed in the simulation model, and, again, the model is replicated 100 times to determine the near optimum volumes (transportation volumes among echelons). Therefore, after 100 replications, 100 feasible solutions are saved in the Microsoft Excel sheets. For each feasible solution, the average total costs are calculated in two ways; by fixing the routes (by closing the non-economic factories and warehouses according to the previous results) and without fixing routes. In this paper, we use the second way because it produces lower costs.

Ten different test problems were created; the size of each test problem is shown in Table 1. All test problems have 4 final products. The total costs include transportation, production, inventory holding and fixed set up costs from supplier to final customer at each echelon. All test problems are generated using uniform distributions, which are depicted in Tables 2 to 5, respectively. Every factory produces four types of product, including four raw materials in the suppliers, four sub-assembled products in the sub-assembly factories, and four final assembled products in the final assembly factories at each echelon. The processing time of raw materials in the suppliers and the sub products in the sub-assembly factories follow a uniform distribution $U(10, 15)$. The processing time of final products in final assembly factories follows a uniform distribution $U(15, 20)$. The customer demand of each product is an integer number uniformly distributed from $U(30, 60)$. Also, the maximum storage capacity of raw materials in the supplier warehouse, the sub products in the sub-assembly factory warehouse, the final product in the final assembly factory warehouse, and the final product in DCs are equal at 70, 70, 75, and 75, respectively.

### *4.1. Tuning the parameters*

The initial parameters of our HSIM-GA include cross over ($P_c$) and mutation ($P_m$), and the initial parameter of our HSIM-SAA is initial temperature ($T_0$), which is the starting temperature point, and the temperature decreasing rate ($\alpha$). We used the Taguchi method in designing the experiments (DOE) [33]. In the Taguchi method, the results are transferred into a measure called a signal to noise ($S/N$) ratio. The formulation of this ratio is different for each objective (maximization or minimization). Eq. (49) represents the ($S/N$) ratio for minimization objectives:

$$S/N = -10 \log \left( 1/n \sum_{i=1}^{n} y_i^2 \right), \tag{49}$$

in which, $n$ and $y_i$ indicate the number of replications and process response values at the $i$'th replication. In the DOE, we chose the orthogonal array of $L_9$ both for HSIM-GA and the HSIM-SAA. The initial parameter values, after the sensitivity analysis of the factors, are shown in Tables 6 and 7. Figures 9 and 10 depict the averaged $S/N$ ratio for each factor level. Also, the optimum combinations of the parameters for each HSIM-META, which include HSIM-GA and HSIM-SAA, are shown in Table 8.

**Table 1.** The size of test problems.

| Problem sizes | Number of suppliers | Number of sub-assembly factory | Number of final assembly factory | Number of DCs | Number of customer |
|---|---|---|---|---|---|
| 1 | 1 | 2 | 2 | 1 | 2 |
| 2 | 2 | 1 | 2 | 2 | 2 |
| 3 | 2 | 2 | 1 | 2 | 3 |
| 4 | 2 | 2 | 2 | 2 | 3 |
| 5 | 3 | 2 | 3 | 2 | 3 |
| 6 | 3 | 3 | 2 | 3 | 3 |
| 7 | 4 | 3 | 5 | 4 | 3 |
| 8 | 4 | 3 | 4 | 4 | 4 |
| 9 | 5 | 4 | 4 | 4 | 4 |
| 10 | 5 | 5 | 5 | 4 | 4 |

**Table 2.** Transportation costs among echelons.

| | Transporter cost from supplier to sub-assembly factory | Transporter cost from sub-assembly factory to final assemble factory | Transporter cost from final assembly factory to DC | Transporter cost from DC to final customer |
|---|---|---|---|---|
| Transporter costs | $U$ (200, 700) | $U$ (400, 800) | $U$ (200, 600) | $U$ (200, 700) |

**Table 3.** Production costs of manufacturing plants at each echelon.

| | Production cost in supplier | Production cost in sub-assembly factory | Production cost in final assembly factory |
|---|---|---|---|
| Production costs | $U$ (1200, 1500) | $U$ (1400, 3800) | $U$ (1500, 3200) |

**Table 4.** Inventory holding costs of manufacturing plants and warehouses at each echelon.

| | Inventory holding cost in supplier | Inventory holding cost in sub-assembly factory | Inventory holding cost in final assembly factory | Inventory holding cost in DC |
|---|---|---|---|---|
| Inventory holding costs | $U$ (50, 80) | $U$ (40, 100) | $U$ (50, 80) | $U$ (60, 90) |

**Table 5.** Fixed set up costs of manufacturing plants and warehouses at each echelon.

| | Supplier | Sub-assembly factory | Final assembly factory | DC |
|---|---|---|---|---|
| Fixed set up costs | $U$ (1200000, 1600000) | $U$ (2000000, 4000000) | $U$ (5000000, 9000000) | $U$ (500000, 800000) |

### *4.2. Analysis of results*

In order to use HSIM-META to obtain near optimum solutions, three different scenarios were developed to link the output data of the simulation model in the tuned-parameter, HSIM-META. The scenarios, as follows, determine how the randomly generated solutions in the simulation model must be used as the initial population in HSIM-META:

- **Scenario 1:** 10 best simulation solutions (regarding their objective function) are used;
- **Scenario 2:** 10 best simulation solutions, together with 10 medium solutions, are use;
- **Scenario 3:** 10 best simulation solutions, 10 medium solutions, and 10 worst solutions are used.

After several experiments using MATLAB software, it was shown that Scenario 1 is the best. Then, we link the output of the first 10 best simulation solutions in tuned-parameter HSIM-META.

To test the performance of HSIM-META, we compared HSIM-META, including HSIM-GA and HSIM-

**Table 6.** The initial parameter ranges in HSIM-GA.

| **Parameters** | **Factor levels** | | |
|---|---|---|---|
| | **1** | **2** | **3** |
| $N_{pop}$ | 300 | 500 | 700 |
| $P_c$ | 0.85 | 0.9 | 0.95 |
| $P_m$ | 0.01 | 0.02 | 0.03 |

**Table 7.** The initial parameter ranges in HSIM-SAA.

| **Parameters** | **Factor levels** | | |
|---|---|---|---|
| | **1** | **2** | **3** |
| $T_0$ | 1000 | 1500 | 2000 |
| $\alpha$ | 0.9 | 0.95 | 0.99 |

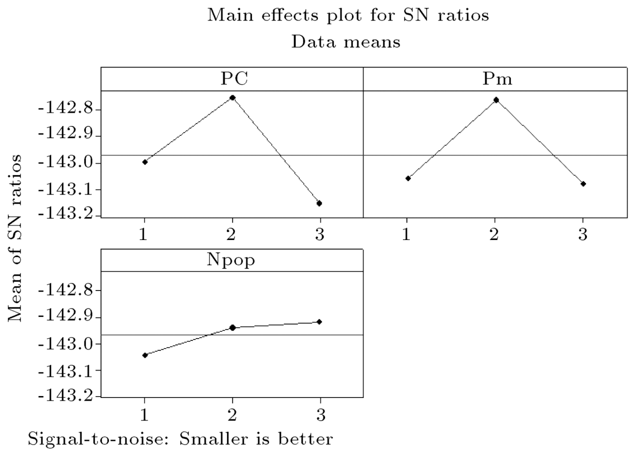


**Figure 9.** Factor level of the proposed HSIM-GA.

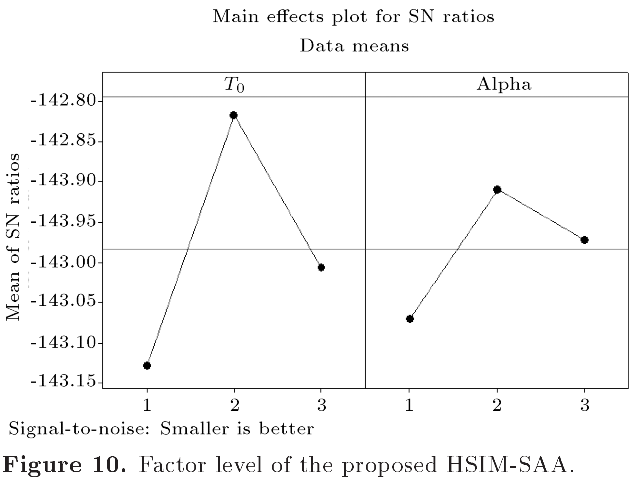


**Figure 10.** Factor level of the proposed HSIM-SAA.

SAA, with general GA and SAA, without using the simulation result as the initial population for the test problems. Also, we utilized the Average Relative Percentage Deviation (ARPD) to compare the algorithms, according to the following formulas:

$$\mathrm{RPD}_j = \frac{Z_s(j) - \min_s(j)}{\min_s(j)} * 100 \qquad j = 1, ..., n, \tag{50}$$

**Table 8.** The optimum parameter levels.

| **Hybrid metaheuristics** | **Parameters** | **Optimum amounts** |
|---|---|---|
| HSIM-GAA | $N_{pop}$ | 500 |
| | $P_m$ | 0.02 |
| | $P_c$ | 0.9 |
| | $P_r = 1 - (P_c + P_m)$ | 0.08 |
| HSIM-SAA | $T_0$ | 1500 |
| | $\alpha$ | 0.95 |

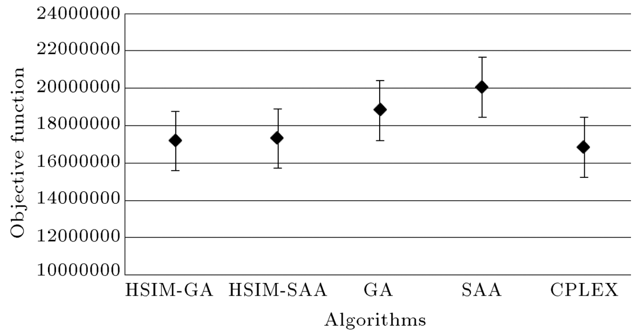


**Figure 11.** The Tukey's Honestly Significant Difference (HSD) for the small sized problems.

$$\mathrm{ARPD} = \frac{\sum_{i=1}^{n} \mathrm{RPD}}{n}, \tag{51}$$

where, $Z_s$ is the objective function value for a given algorithm, $\min_s$ is the best value of the objective function between both algorithms, and $n$ is the row number of small size or large size problems.

The results of the proposed HSIM-GA, HSIM-SAA, GA, and SAA are presented in Table 9. We designed 50 cases for the test problems. Each problem size was replicated five times and the optimum solutions of the objective function and the CPU time were recorded. To investigate the solution quality of the proposed algorithms, the optimum solution of each test problem is obtained by CPLEX. The last two columns of Table 9 report the objective function and CPU time for the CPLEX. We limited the computational time of CPLEX to 2000 seconds. Not obtaining the global optimum solution within this time limitation is meant as "Not available (Out of CPU time)".

In order to statistically compare algorithm quality, Tukey's Honestly Significant Difference (HSD) test is applied. Using this test, we are able to reveal significant differences between algorithms. As shown in Figure 11, the differences are not very meaningful among HSIM-GA, HSIM-SAA, GA, SAA and CPLEX for the small-sized problems. Thus, it can be concluded that two meta-heuristics, along with the others, are able to find good solutions.

Figures 12 and 13 show the Average RPD (ARPD) of the objective function and the CPU time

**Table 9.** The computational results for Objective Function (OF) and CPU time.

| Problem sizes | Test problem | HSIM-GA | | HSIM-SAA | | GA | | SAA | | CPLEX | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | OF | CPU time (S) | OF | CPU time (S) | OF | CPU time (S) | OF | CPU time (S) | OF | CPU time (S) |
| 1 | 1 | 14563218 | 121 | 14438903 | 112 | 15447921 | 208 | 16653210 | 165 | 14273210 | 115 |
| | 2 | 13573422 | 119 | 13564380 | 121 | 14896356 | 203 | 15567911 | 160 | 13159012 | 118 |
| | 3 | 13478032 | 124 | 13659903 | 118 | 14784487 | 215 | 15312175 | 166 | 13227631 | 123 |
| | 4 | 14489046 | 122 | 14278325 | 117 | 15658104 | 211 | 16405476 | 169 | 13873196 | 117 |
| | 5 | 13736938 | 120 | 13972207 | 123 | 14812143 | 209 | 15446532 | 164 | 13557290 | 122 |
| 2 | 6 | 16663218 | 163 | 16438903 | 156 | 17447921 | 277 | 18653210 | 222 | 16117691 | 158 |
| | 7 | 15573422 | 172 | 15564380 | 161 | 16896356 | 282 | 17567911 | 217 | 15317762 | 161 |
| | 8 | 15478032 | 166 | 15659903 | 159 | 16784487 | 281 | 17312175 | 216 | 14984720 | 154 |
| | 9 | 16489046 | 174 | 16278325 | 153 | 17658104 | 274 | 18405476 | 217 | 15870313 | 155 |
| | 10 | 15736938 | 161 | 15672207 | 166 | 16812143 | 278 | 17446532 | 224 | 15228035 | 160 |
| 3 | 11 | 18115421 | 253 | 18327645 | 234 | 19754328 | 406 | 20216674 | 321 | 17748902 | 232 |
| | 12 | 17904512 | 248 | 18115437 | 242 | 19595632 | 401 | 20674328 | 325 | 17511693 | 227 |
| | 13 | 19226398 | 257 | 19794321 | 251 | 20463206 | 389 | 22893217 | 327 | 18784322 | 236 |
| | 14 | 19468703 | 249 | 19359023 | 239 | 20234002 | 403 | 22704310 | 328 | 18980331 | 233 |
| | 15 | 18326812 | 251 | 18216732 | 247 | 19438721 | 408 | 20405611 | 330 | 17820346 | 225 |
| 4 | 16 | 20225489 | 371 | 20874321 | 357 | 23412387 | 559 | 25217632 | 478 | 19773904 | 331 |
| | 17 | 19548732 | 378 | 19443211 | 348 | 22683279 | 544 | 24438791 | 477 | 19125477 | 327 |
| | 18 | 19763221 | 383 | 20126532 | 363 | 21974591 | 551 | 24690034 | 485 | 19317021 | 337 |
| | 19 | 20437621 | 379 | 21553176 | 361 | 23542176 | 547 | 25517904 | 483 | 19763488 | 329 |
| | 20 | 20773265 | 385 | 20821763 | 357 | 23789033 | 543 | 25711890 | 475 | 19653382 | 334 |
| 5 | 21 | 23435105 | 603 | 23326743 | 578 | 27674802 | 878 | 29763485 | 810 | NA[a] | NA |
| | 22 | 24658214 | 596 | 24789432 | 582 | 28727628 | 889 | 30715543 | 818 | NA | NA |
| | 23 | 24673268 | 610 | 23810547 | 585 | 29043557 | 883 | 31104367 | 807 | NA | NA |
| | 24 | 23675523 | 588 | 23657854 | 590 | 27527643 | 886 | 29563498 | 821 | NA | NA |
| | 25 | 23326548 | 594 | 23214892 | 579 | 28032564 | 890 | 30124461 | 811 | NA | NA |
| 6 | 26 | 28546739 | 733 | 28045671 | 714 | 31305781 | 1067 | 34923420 | 947 | NA | NA |
| | 27 | 27678494 | 742 | 27558902 | 725 | 29078432 | 1063 | 33664983 | 952 | NA | NA |
| | 28 | 28345329 | 748 | 28653332 | 731 | 32763456 | 1071 | 35217054 | 943 | NA | NA |
| | 29 | 27768932 | 739 | 27614736 | 720 | 29873490 | 1069 | 32674389 | 958 | NA | NA |
| | 30 | 27432176 | 746 | 27667235 | 737 | 30236726 | 1082 | 33021472 | 949 | NA | NA |
| 7 | 31 | 32456721 | 1045 | 32768534 | 1021 | 36237653 | 1393 | 41234761 | 1293 | NA | NA |
| | 32 | 33568934 | 1048 | 33876421 | 1032 | 38763219 | 1402 | 42658940 | 1298 | NA | NA |
| | 33 | 33789054 | 1046 | 33671187 | 1018 | 39012378 | 1388 | 42895476 | 1303 | NA | NA |
| | 34 | 32784537 | 1049 | 33151239 | 1036 | 37413471 | 1406 | 40763487 | 1296 | NA | NA |
| | 35 | 32894542 | 1043 | 33458716 | 1026 | 36590325 | 1390 | 41553489 | 1310 | NA | NA |
| 8 | 36 | 37636310 | 1282 | 37434550 | 1256 | 40764376 | 1634 | 44957432 | 1513 | NA | NA |
| | 37 | 37675323 | 1291 | 37922567 | 1268 | 40857821 | 1641 | 43216786 | 1510 | NA | NA |
| | 38 | 37819340 | 1275 | 37363125 | 1247 | 39976535 | 1637 | 44678975 | 1543 | NA | NA |
| | 39 | 38214831 | 1284 | 38637712 | 1261 | 41045684 | 1644 | 46659853 | 1521 | NA | NA |
| | 40 | 38139323 | 1287 | 38443257 | 1244 | 41456723 | 1639 | 45321765 | 1532 | NA | NA |
| 9 | 41 | 43245781 | 1576 | 44672390 | 1523 | 47412265 | 2054 | 51356722 | 1911 | NA | NA |
| | 42 | 43763218 | 1581 | 44890327 | 1512 | 46803265 | 2047 | 52278360 | 1918 | NA | NA |
| | 43 | 43678902 | 1567 | 44523311 | 1536 | 47335812 | 2061 | 51934462 | 1922 | NA | NA |
| | 44 | 44669216 | 1583 | 45704571 | 1524 | 49327634 | 2056 | 54603265 | 1924 | NA | NA |
| | 45 | 44832368 | 1580 | 45769362 | 1533 | 48763341 | 2066 | 55221783 | 1932 | NA | NA |
| 10 | 46 | 51526295 | 2023 | 52867340 | 1995 | 56247642 | 2607 | 62832170 | 2453 | NA | NA |
| | 47 | 50742387 | 2034 | 51512376 | 1978 | 55864376 | 2616 | 60336529 | 2448 | NA | NA |
| | 48 | 51762344 | 2026 | 52213275 | 1985 | 57562178 | 2624 | 63015677 | 2464 | NA | NA |
| | 49 | 50448745 | 2041 | 51982300 | 1991 | 54565903 | 2619 | 61690434 | 2457 | NA | NA |
| | 50 | 51736782 | 2037 | 52112187 | 1987 | 56537645 | 2625 | 62589932 | 2461 | NA | NA |

[a]NA: Not Available (out of CPU time).

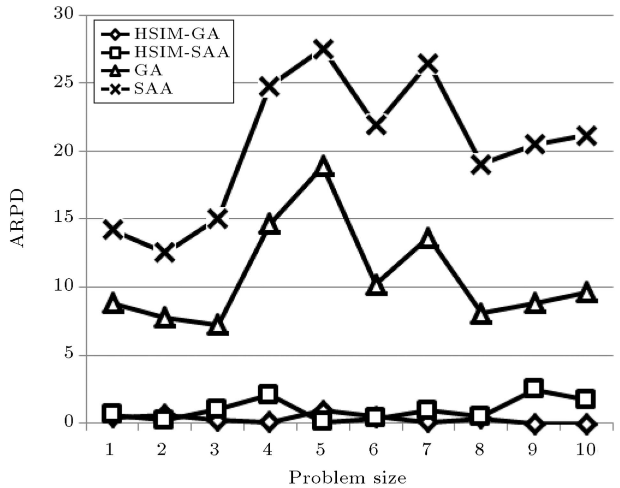


**Figure 12.** The ARPD for objective function of the algorithms.

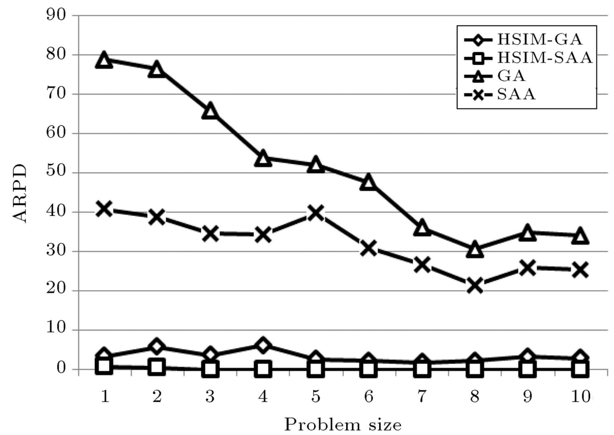


**Figure 13.** The ARPD for computational time of the algorithms.

of the proposed algorithms. According to the ARPD factor, HSIM-GA has better quality, with 0.54, 10.29, and 19.84 deviations, against HSIM-SAA, GA and SAA, respectively. In terms of the CPU time index, the HSIM-SAA obtained better CPU time, with 3.33, 50.75 and 31.68 deviations, against HSIM-GA, GA and SAA, respectively. Also, Figures 14 and 15 show the 95% confidence intervals of RPD for the objective function and CPU time indices, respectively. To sum up, we can see that HSIM-GA gives better results than all other algorithms in terms of the objective function, and the HSIM-SAA has better results regarding the CPU time index for all problem sizes.

## 5. Conclusion and suggestions for future work

In this paper, a new model and two hybrid algorithms were developed to address the so-called SCN problem. The algorithms combined a simulation technique with two metaheuristic algorithms (GA and SAA), called HSIM-META, to solve such an NP-hard problem,

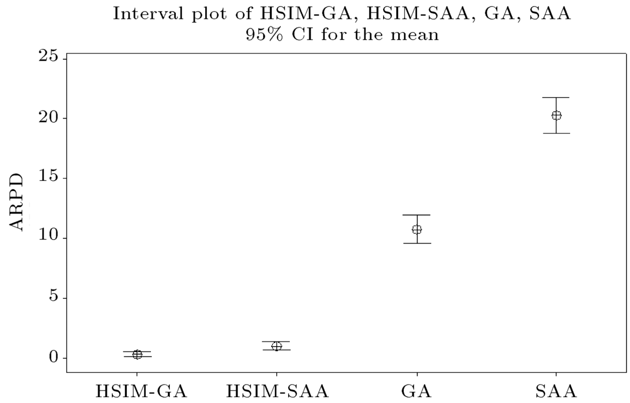


**Figure 14.** 95% confidence intervals of RPD of objective function.

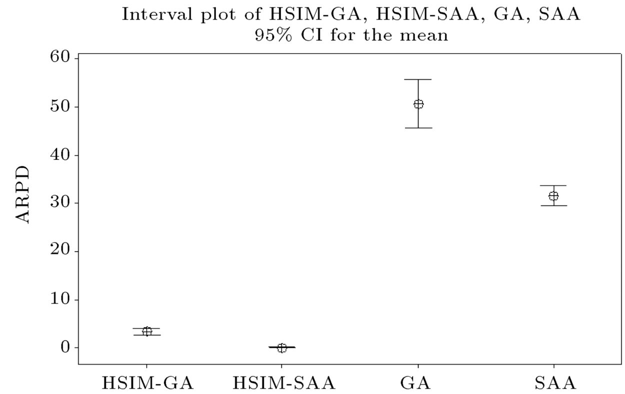


**Figure 15.** 95% confidence intervals of RPD of CPU time.

which is the main contribution of the current research. First, the mathematical programming model of the SCN was developed, assuming limited capacities for the model warehouses, and then the corresponding simulation model was built. The simulation model was used to determine the best production-distribution routes and to close non-economic facilities and warehouses in the SCN model. After fixing the routes, several random feasible solutions were generated by the simulation model using 3 different scenarios and by selecting the best one. Then, 10 best feasible solutions were selected as the initial population for HSIM-META. This version of OVS is a novel approach in OVS literature. It benefits from the ability of the simulation technique to produce several random feasible solutions and also from the optimization engine of metaheuristics. To test the performance of our HSIM-META algorithm, 50 numerical test problems were developed and solved using the algorithms. As the results show, combining simulation with the metaheuristic algorithms has the advantages of both methods and can escape from the local optimal solution and find near optimal solutions. Analysis of the results shows that the HSIM-META containing HSIM-GA and HSIM-SAA has better quality of solutions, regarding the objective function and

CPU time, than general GA and SAA. According to the ARPD comparisons, HSIM-GAA has better quality solutions than GA, SAA, and HSIM-SAA in terms of the objective function, and the HSIM-SAA is faster in comparison to GA, SAA, and HSIM-GA. For future research, other metaheuristic algorithms can be considered and linked to the simulation technique. Also, shortage costs can be investigated in the SCN to develop a new mathematical model. To expand the current model, our suggestion is to consider the pricing factor in the model, i.e. consider some active competitors in the market, whose sales volume and prices can affect product prices and demands, which could make the model much more realistic. In this new concept, which integrates SCN with market planning, an agent-based simulation modelling is highly recommended.

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