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# Improved Meta-Heuristic for Multi-Objective Integrated Procurement, Production and Distribution Problem of Supply Chain Network Under Fuzziness Uncertainties

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**Abstract:** In this study, we devoted a design under uncertainty of a supply chain network composed of multiple suppliers, multiple plants, multiple distributors and multiple customers. The proposed model is a bi-objective mixed integer linear programming which consider several constraints and optimize the total costs including the procurement, production, storage and distribution costs as well as maximize on-time deliveries. In order to model a similar problem to the real planning problems, the objective function coefficients (e.g., procurement cost, production cost and inventory holding) and other parameters (e.g., demand and production capacity), are all supposed triangular fuzzy numbers. Besides, a hybrid credibility-based model is constructed for the problem, i.e., expected value and chance constrained models. Moreover, the construction of the crisp equivalent model is based on different properties of the credibility theory. The resulted crisp equivalent model is a bi-objective MILP. To transform the crisp BOMILP to a single objective MILP model, we propose the LP-metric method. To solve the planned model for largest instances, we tend to propose a hybrid algorithm based on a recent metaheuristic called Hunger Game Search (HGS). This algorithm employs the so-called chaotic search to prevent premature convergence and entrapment in local optima. Finally, the efficiency and sensitivity of the proposed model are justified through the numerical results.

**Keywords:** Hungry Search Game, Chaotic Search, Supply Chain Network, Procurement-Production- Distribution, Credibility Theory

## Introduction

Given the current trends in globalization Douaioui *et al.* (2018), many companies are increasingly sourcing, producing and marketing their products around the world. For many of them, success depends on a personalized production, in a short time and at a good price. Recently, supply chain management has been proven as the best solution to meet these contradictory constraints. As a result, many researchers focus on planning and scheduling of supply chain in order to maximize the overall performance. This integration not only reduces the number of steps in the process but also tends to eliminate the inherent barriers between the various functions to see overall optimization Douaioui *et al.* (2021). Our research is in line with this trend, intending to study the problem of

integration of functions such as procurement, production and distribution of the supply chain. It should also be noted that the challenges associated with the variability of demand are accentuated by the length of the manufacturing period and the transport conditions. All these factors make planning and scheduling of the supply chain a challenged task. The problems cited above are often dealt with under specific conditions. As reported by Klibi *et al.* (2010), any supply chain planning that relies on deterministic conditions risks losing its durability. They also mention that in some cases, it is not enough for the company to consider usual parameters such as demand, prices, or other parameters such as random variables, but undesirable events such as terrorist attacks and natural disasters. Consequently, it's necessary to develop a adequate strategy that integrates uncertainty into supply chain network.

In This study's most important contributions are as follows: (i) Propose a MILP formulation for integrating the procurement, production and distribution problem within the supply chain network, (ii) Take into account the different source of uncertainty such as costs, demand, production capacity and safety stock level, (iii) Utilize the credibility theory as an appropriate framework to deals with the uncertainty, (iv) Overcome the problems related to use a single model such as expected value by taking the advantages of both models. (v) The developed model is a bi-objective model with conflicting objectives. We use the LP-metric as one of the well-known MCDM methods to transform the model into a single objective model. (vi) To solve the developed model in the largest instances, a hybrid metaheuristic based on a recent algorithm called Hunger Game Search (HGS) is proposed. This algorithm employs the so-called chaotic search to prevent entrapment in local optima and the precipitate convergence. (vii) Testing the sensitivity and robustness of the proposed solution. The paper is organized as follows.

## Literature Review

### Supply Chain Network

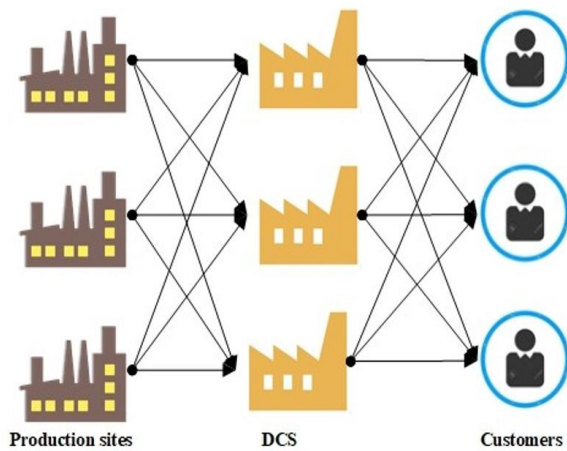
This study highlights the problem of integrating functions of supply chain namely procurement, production and distribution and which has several geographically dispersed suppliers, production sites, distribution centers and customers. Each supplier has a limited procurement capacity. Each production has a limited production time capacity which depends essentially on the installed processing units and the speed of each unit. The utilization of a production unit generates production and set-up costs that must be integrated into the model. In general, the optimization procedure must consider the other costs such as holding inventory, transportation and backorder. The model considers also the on-time delivery to minimize too late the product of each customer. Figure 1 and 2 represents an illustration of the supply chain network. Regarding the significant increase in supply chain complexities, several researchers developed and solved models by the meta-heuristic approach. Among them, Samadi *et al.* (2018) develop a multi-objective closed-loop supply chain, which has considered the total cost, environmental impacts of the network and the social objective. Abdi *et al.* (2021) address a new closed-loop supply chain model using the two-stage stochastic programming formulation. The authors solve the model by Whale Optimization Algorithm (WOA) and Particle Swarm Optimization (PSO), the used meta heuristic performance outperformed the Genetic Algorithm (GA) and Simulated Annealing (SA). Bottani *et al.* (2019) propose a new resilient food supply chain design problem, the authors propose a bi-objective mixed-integer programming formulation. The paper aims to minimize the lead time and maximize the total profit. The authors use Ant Colony Optimization (ACO) to solve the problem in a large-scale

network. Sarkar *et al.* (2019) address a multi-attribute closed-loop supply chain model to maximize total profit and minimize the emissions of CO<sub>2</sub>. The paper uses three meta-heuristics; Genetic algorithm, Interior point optimization algorithm and Particle swarm optimization to solve the model in large size instances. Khalifehzadeh *et al.* (2019) present a multi-echelon production-distribution network model in the multi-time horizon, the model aims to minimize the total delivery lead time and maximizes the total profit. The proposed solution shows that the performance is improved by applying the Firefly Algorithm and Ranking Genetic Algorithm, respectively. Regarding complexity and the multiplication of interevent in supply chain network, several researchers like this study contribute the new meta-heuristic to improve the overall performance.

### Supply Chain Management Under Uncertainty

The theory of probability proved to be the old theory to deal with uncertain parameters. However, in practice, several disadvantages are related to the use of the probability theory (1) need for a sufficient and reliable history and (2) problem of modeling of subjective parameters Pishvae and Torabi (2010), Liu and Kao (2004). The fuzzy set theory (FST) is an alternative to treat uncertainty by giving local preferences into account in optimization problems. In the fuzzy set theory, there are three forms of measures for a fuzzy event namely the possibility, the necessity and the credibility measure. Possibility theory is considered as a counterpart of probability theory Dubois *et al.* (2004) and is widely used in literature to treat fuzzy variables. Further, it is conflicting with the law of excluded middle and the law of contradiction. To over this challenge, (Liu and Liu, 2002) proposed the credibility measure. This measure is a more reasonable fuzzy inequality indicator than the possibility and necessity because it compensates for their disadvantages. For example, an event with a maximum possibility of 1 might not happen while an event with maximum credibility of 1 occurs. Furthermore, a fuzzy event with maximum possibility 1 sometimes carries no information while a fuzzy event with maximum credibility 1 means that the event will happen at the greatest chance Huang (2006). In the optimization process for management and planning, it is usually assumed that the credibility level should be super than 0.5 in response to avoiding un-satisfactions and overtaking the risks Pishvae *et al.* (2012). X supposed be a fuzzy variable with membership function  $m(x)$  and  $t$  a real number. Based on (Liu and Liu, 2002) the credibility measure is characterized as Eq. 1:

$$Cr\{\xi \leq t\} = \frac{1}{2} \left( \sup_{x \leq t} \mu(x) + 1 - \sup_{x > t} \mu(x) \right), \quad (1)$$



**Fig. 1:** Supply chain network

Noteworthy, since  $Pos\{\xi \leq t\} = \sup_{x \leq t} \mu(x)$  and  $Nec\{\xi \leq t\} = 1 - \sup_{x > t} \mu(x)$ , the credibility measure can also be defined as Eq. 2:

$$Cr\{\xi \leq t\} = \frac{1}{2} (Pos\{\xi \leq t\} + Nec\{\xi \leq t\}) \quad (2)$$

Appropriately, the credibility measure can be expressed as an average of the possibility (Pos) and necessity (Nec) measures. In addition, the expected value of  $\xi$  is characterized as Eq. 3 Liu and Liu (2002):

$$E[\xi] = \int_0^{\infty} Cr\{\xi \leq t\} dt - \int_{-\infty}^0 Cr\{\xi \leq t\} dt, \quad (3)$$

Now, suppose that  $\xi$  is a triangular fuzzy number expressed by three points as  $\xi = (a, b, c)$ . Depending on Eq. (13), the expected value of  $E[\xi] = \frac{a + 2 * b + c}{4}$  and the credibility measures are characterized by Eq. 4 and 5:

$$Cr\{\xi \leq t\} = \begin{cases} 0, & \text{if } t \leq a \\ (t-a)/2(b-a), & \text{if } a < t \leq b, \\ (c-2b+t)/2(c-b), & \text{if } b < t \leq c \\ 1, & \text{if } t > c \end{cases} \quad (4)$$

$$Cr\{\xi \geq t\} = \begin{cases} 1, & \text{if } t \leq a \\ (c-2b+t)/2(c-b), & \text{if } a < t \leq b, \\ (t-a)/2(b-a), & \text{if } b < t \leq c \\ 0 & \text{if } t > c \end{cases} \quad (5)$$

Based on (4) and (5), it can be demonstrated Zhu and Zhang (2009) that if  $\xi$  is a triangular fuzzy number and  $\beta > 0.5$  correspondingly:

$$Cr\{\xi \geq t\} \geq \beta \Leftrightarrow (2\beta - 1)c + (2 - 2\beta)b, \quad (6)$$

$$Cr\{\xi \leq t\} \geq \beta \Leftrightarrow (2\beta - 1)a + (2 - 2\beta)b, \quad (7)$$

Equation 6 and 7 can be performed and a lot of conveniently when compared to a-critical values proposed by Liu and Kao (2004), to convert fuzzy chance constraints to the equivalent crisp model. In credibility programming, there are three forms of credibility approaches: The chance constrained programming, the expected value Liu and Liu (2002) and the dependent chance constrained programming Liu (1999). The chance constrained programming model uses the expected value operator for each imprecise coefficient. It can be applied easily without increasing the complexity of the original model compared to the other two methods, but at the same time, it has no control over the level of confidence of the fuzzy chance constraint. The second model can control the level of satisfaction of the fuzzy chance constraint by using the concept of b-level. Although increases the complexity of the model since it adds a new constraint for each objective function of the main model. In this study, we combined the expected value operator and the chance constraint to deal with the uncertain parameters of the objective functions and constraints. The reason behind this consolidation is that the expected value operator does not need any additional data for objective function or the ideal solution and is also benefited from advantages of the chance-constrained programming the approach to control the level of satisfaction of the fuzzy chance constraint by using the concept of  $\alpha$ -level Pishvae *et al.* (2012).

### Mathematical Formulation

According to the above-mentioned descriptions and justifications, the proposed credibility based fuzzy mathematical programming with expected value operators for integrated production-distribution in the supply chain network. The basic considerations of the problem under consideration are summarized, as follows: The planning horizon is known and divided into a set of period  $t \in T$  A set of suppliers  $s \in S$ , production sites  $p \in P$ , a set of DCs  $d \in D$  and a set of customers  $c \in C$  A set of products  $k \in K$ .

The key decision variables are:

- The set-up of products to units in each period  $t$
- The quantity produced of each product on each processing unit at each period  $t$
- The total quantity dispatched between production sites-DCs and between DCs-Customers respectively
- The inventory levels of each product at sites and distribution center DCs at the end of each period
- The backorder quantity of each product  $p$  provided by the customer at each period

### Indices and Sets

- $s$ : Index used for a supplier  $s = 1, \dots, S$
- $r$ : Index used for a raw material  $r = 1, \dots, R$
- $p$ : Index used for a plant  $p = 1, \dots, P$
- $k$ : Index used for a finished product  $k = 1, \dots, K$
- $d$ : Index used for a Distribution Center (DC)  $d = 1, \dots, D$
- $c$ : Index used for a customer  $c = 1, \dots, C$
- $t$ : Index used for a planning period  $t = 1, \dots, T$

### Indices and Sets

- $\overline{Scap}_{r,s,t}$ : Fuzzy capacity of supplier  $s$  for providing raw material  $r$  in period  $t$
- $\overline{DC}_{k,c,t}$ : Fuzzy demand of product  $k$  required by customer  $c$  in period  $t$
- $\overline{\eta}_{r,s,p,t}$ : Fuzzy on-time delivery rate of raw material  $r$  offered by supplier  $s$  to plant  $p$  in periods time  $t$
- $\overline{BOC}_{p,c,t}$ : Fuzzy backorder cost per unit of product  $p$  at customer  $c$  in period  $t$
- $\overline{SIRP}_{r,p,t}$ : Fuzzy inventory holding costs for raw material  $r$  in plant  $p$  in period  $t$
- $\overline{CSKS}$ : Fuzzy parameter of the unit cost of configuring the production line to produce product  $k$  in plant  $p$  during period  $t$
- $\overline{CIKD}_{k,d,t}$ : Fuzzy inventory holding cost for product  $k$  in plant  $p$  in period  $t$
- $\overline{CIKD}_{k,d,t}$ : Fuzzy inventory holding costs for product  $k$  in DC  $d$  in period  $t$
- $\pi_k$ : Volume of products
- $\pi_r$ : Volume of raw material
- $\overline{pt}_{k,p,t}$ : Fuzzy production time for product  $k$  of plant  $p$  in period  $t$
- $\overline{st}_{k,p,t}$ : Fuzzy set-up time for product  $k$  of plant  $p$  in period  $t$
- $\overline{TT}_{p,t}$ : Fuzzy maximal available time in plant  $p$  at time period  $t$
- $\overline{CKP}_{k,p,t}$ : Fuzzy production cost for product  $k$  of plant  $p$  in period  $t$
- $\overline{CKS}_{k,p,t}$ : Fuzzy set-up cost for product  $k$  of plant  $p$  in period  $t$
- $\overline{TCSP}_{r,s,p,t}$ : Fuzzy cost for transferring raw material from supplier  $s$  to plant  $p$  in period  $t$
- $\overline{TCPD}_{r,s,p,t}$ : Fuzzy cost for transferring finished product from plant  $p$  to distribution center DC  $d$  in period  $t$

- $\overline{TCDC}_{k,d,c,t}$ : Fuzzy costs for transferring finished products from distribution center DC  $d$  to customer  $c$  in period  $t$
- $\overline{PRcap}_{r,p,t}$ : Fuzzy capacity of storage of warehouse plant  $p$  related to raw material in period  $t$
- $\overline{PKcap}_{p,t}$ : Fuzzy capacity of storage of warehouse plant  $p$  related to finished product in period  $t$
- $\overline{DKcap}_{p,t}$ : Capacity of storage of warehouse DC  $d$  related to finished product in period  $t$
- $\overline{\lambda}_{k,d,c,t}$ : Fuzzy on-time delivery rate of product  $k$  offered by distribution center  $d$  to customer  $c$  in period time  $t$
- $\overline{T}_{k,c,t}^{acc}$ : Minimum acceptable on-time delivery rate of customer  $c$  for product  $k$  in period  $t$
- $\overline{\beta}_{k,c,t}$ : Fuzzy maximum backlogging quantity permitted of product  $k$  of customer  $c$  in period  $t$

### Decision Variables

- $X_{k,p,t}$ : 1-if product  $k$  is produced by plant  $p$  in period  $t$
- $\overline{IRP}_{r,p,t}$ : Inventory level of product  $r$  in plant  $p$  at the end of period  $t$
- $\overline{IKP}_{k,p,t}$ : Inventory level of product  $k$  in plant  $p$  at the end of period  $t$
- $\overline{IKD}_{k,d,t}$ : Inventory level of product  $k$  in DC  $d$  at the end of period  $t$
- $\overline{QRSP}_{r,s,p,t}$ : Quantity of raw material  $r$  dispatched from supplier  $s$  to plant  $p$  in period  $t$
- $\overline{QKP}_{k,p,t}$ : Quantity of finished product  $k$  produced in plant  $p$  in period  $t$
- $\overline{QKPD}_{k,p,d,t}$ : Quantity of finished product  $k$  dispatched from plant  $p$  to DC  $d$  in period  $t$
- $\overline{QKDC}_{r,d,c,t}$ : Quantity of finished product  $k$  dispatched from DC  $d$  to customer  $c$  in period  $t$
- $\overline{BQKC}_{k,c,t}$ : Quantity of backorder for product  $k$  incurred by customer  $c$  in period  $t$

### Objective Functions

We consider two important objectives in our supply chain network problem:

- (i): Minimization of Total Cost of logistics (TC)
- (ii): The maximization of on-time deliveries of raw materials

The first objective (TC) is the principal aim of the major companies. The objective is to minimize the cost in different operation of supply chain and to maximize the exploitation servals resources. It consists mainly of the total costs such as: Procurement costs, Inventory costs, transportation costs and Backorder costs.

$$\begin{aligned}
 Min OF_1 = & \sum_{r \in R} \sum_{s \in S} \sum_{p \in P} \sum_{t \in T} E[\overline{TCSPr, s, p, t}] * QRS P_{r, s, p, t} \\
 & + \sum_{r \in R} \sum_{p \in P} \sum_{t \in T} E[\overline{CIRP r, p, t}] * IRP_{r, p, t} \\
 & + \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} E[\overline{CIKP}_{k, p, t}] * IKP_{k, p, t} \\
 & + \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} E[\overline{CIKP}_{k, p, t}] * IKP_{k, p, t} \\
 & + \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} E[\overline{CKP}_{k, p, t}] * QKP_{k, p, t} \\
 & + \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} E[\overline{CSKP}_{k, p, t}] * X_{r, p, t} \\
 & + \sum_{k \in K} \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} E[\overline{TCPD}_{k, p, d, t}] * QKPD_{k, p, d, t} \\
 & + \sum_{k \in K} \sum_{d \in D} \sum_{c \in C} \sum_{t \in T} E[\overline{TCDC}_{k, d, c, t}] * QKDC_{k, d, c, t} \\
 & + \sum_{k \in K} \sum_{c \in C} \sum_{t \in T} E[\overline{BOC}_{k, c, t}] * BOC_{k, c, t}
 \end{aligned} \tag{8}$$

The second Objective function (OTD) is considered to maximize the on-time deliveries to ensure a continuous flow of production and minimize the plant stoppages due to unavailability of raw materials items. In this study, we have assumed that the demands, supplier capacity and all units' costs (i.e., production, transportation, storage and backorder) are all fuzzy variables. So, the total costs and the on-time deliveries of raw materials are also fuzzy variables. In the process of search an optimal solution, it's not sufficient to maximize on-time deliveries and minimize the total costs, but it's primordial to specify the fuzzy variable. Therefore, we develop a new model within the framework of credibility theory given as follows:

$$Max OF_2 = \sum_{e \in R} \sum_{s \in S} \sum_{p \in P} \sum_{t \in T} E[\overline{\eta}_{r, s, p, t}] * QRS P_{r, s, p, t} \tag{9}$$

### Constraints

Constraint 10 granted that the total quantity of raw materials that can be transported from each available supplier to any manufacturer cannot surpass the fuzzy supplier capacity:

$$\sum_{r \in R} QRS P_{r, s, p, t} \leq E[\overline{Scapr, s, t}]; \forall s \in S, t \in T \tag{10}$$

Constraints (11-12) give the inventory balance equations of raw materials and finished products in plants respectively.

$$\begin{aligned}
 IRP_{r, p, t-1} + \sum_{s \in S} QRS P_{r, s, p, t} - \sum_{k \in K} \alpha_{r, k} \\
 QKP_{k, p, t}; \forall r \in R, p \in P, t \in T
 \end{aligned} \tag{11}$$

$$\begin{aligned}
 IRP_{k, p, t} = IKP_{k, p, t-1} + QKP_{k, p, t} \\
 - \sum_{d \in D} QKD_{k, p, d, t}; \forall k \in K, p \in P, t \in T
 \end{aligned} \tag{12}$$

Constraint Eq. 13 ensure the inventory balance equations of finished products in DCs:

$$\begin{aligned}
 IKD_{k, d, t} = IRP_{k, d, t-1} + \sum_{p \in P} QKD_{k, p, d, t} - \\
 \sum_{c \in C} QKC_{k, d, c, t}; \forall k \in K, d \in D, t \in T
 \end{aligned} \tag{13}$$

Constraint Eq. 14 guarantees that the fuzzy total required time to produce the products cannot exceed the fuzzy total available time:

$$\begin{aligned}
 \sum_{k \in K} E[\overline{pt}_{k, p}] * QKP_{k, p, t} + \sum_{k \in K} E[\overline{st}_{k, p}] * X_{k, p, t} \leq \\
 E[\overline{TT}_{k, p}]; \forall k \in K, p \in P
 \end{aligned} \tag{14}$$

Constraint Eq. 15 shows the quantity of the raw material shipped to plant p from suppliers plus the inventory level of raw material in plant p in period t is limited to the capacity of plant:

$$\begin{aligned}
 \sum_{s \in S} \sum_{r \in R} \pi_r * QRS P_{r, s, p, t} + \sum_{r \in R} \pi_r * IRP_{r, p, t} \leq \\
 PRcap_{p, t}; \forall d \in D, t \in T
 \end{aligned} \tag{15}$$

Constraint Eq. 16 assure that the volume of production must be less than or equal to the total storage capacity of the plant p in time period t:

$$\sum_{k \in K} V_k * IKP_{k, p, d, t} \leq PKcap_{p, t}; \forall p \in P, t \in T \tag{16}$$

Constraint Eq. 17 granted that the quantity of each product shipped to each distribution center from any plant plus the inventory level of product k in the distribution center d in period t is limited by the capacity storage of the distribution center:

$$\begin{aligned}
 \sum_{p \in P} \sum_{k \in K} V_k * QKD_{k, p, d, t} + \sum_{k \in K} V_k * IKD_{k, d, t} \leq \\
 DKcap_{d, t}; \forall d \in D, t \in T
 \end{aligned} \tag{17}$$

Constraint Eq. 18 represents that the backlog level. In the last period t equal to backlog level of the past period plus the expected value of demand minus the total received from DCs:

$$\begin{aligned}
 BQKC_{k, c, t} = BQKC_{k, c, t-1} + E[\overline{DC}_{k, c, t}] \\
 - \sum_{e \in C} QKC_{k, d, c, t}; \forall k \in K, t \in T
 \end{aligned} \tag{18}$$

Constraint Eq. 19 is concerned with the backlog balance equation at the last time period:

$$\sum_{c \in C} QKC_{k, d, c, t} - BQKC_{k, c, T-1} \leq E[\overline{DC}_{k, c, t}]; \forall k \in K, t \in T \tag{19}$$

Constraint in Eq. 20 guarantees that the quantity of a product dispatched to each customer in a period cannot exceed his/her demand:

$$\sum_{c \in C} QKC_{k,d,c,t} \leq \overline{DC}_{k,c,t}; \forall k \in K, c \in C, t \in T \quad (20)$$

Constraint 21 guarantees that the backorder quantities of product k in the distribution centers (DC) d in time period t is limited to a percentage of the demand of that period:

$$BQKC_{k,c,t} \leq \beta_{k,c,t} * E \left[ \overline{DC}_{k,c,t} \right]; \forall k \in K, c \in C, t \in T \quad (21)$$

Constraint 22 guarantees that the on-time delivery of finished products from DCs to customer c:

$$\sum_{c \in C} \left( 1 - E \left[ \lambda_{k,d,c,t} \right] \right) * QKC_{k,d,c,t} \leq \left( 1 - T_{k,c,t}^{acc} \right) * E \left[ \overline{DC}_{k,c,t} \right]; \forall k \in K, c \in C, t \in T \quad (22)$$

Constraint 23 defines the status of the decision variables:

$$\begin{aligned} X_{k,p,t} &\in \{0,1\}; \\ IRP_{r,p,t}; IKP_{k,p,t}; IKD_{k,d,t}; QRS P_{r,s,p,t}; \\ QKP_{k,p,t}; QKPD_{k,p,d,t}; QKDC_{r,s,p,t} BQKC_{k,c,t} &\geq 0 \end{aligned} \quad (23)$$

## The Solution Methods

### Transforming a Multi-Objective Problem into a Single Objective

Generally, there is a difference between the single-objective meta-heuristics and multi-objective meta-heuristics: The multi-objective meta-heuristics provides a compromise between contradictory objective functions that result in a set of optimal non-dominated solutions called Pareto-optimal solutions, while the single-objective metaheuristics upon obtaining a single optimal solution are proved. Any objective can be modified only at the cost of ruining another objective/s according to each Pareto optimal solution. So, for all that, the decision-makers try to articulate their posterior preference or prior over the objectives based on multi-objective techniques. Thus, the scalarization is used to transform a multi-objective problems to single-objective problems. In this study to solve the mathematical model, the Compromise Programming (CP) method is considered. The aim of this method is to search a solution that comes as close as possible to optimal (ideal) values of each objective function. The closeness is defined by L-p distance metric as follows:

$$\min Z(x) = \left( \sum_{i=1}^k \left( \frac{f_i^* - f_i}{f_i^*} \right)^r \right)^{\frac{1}{r}} \quad (24)$$

In which  $f_1, f_2, \dots, f_k$  are different and conflicting objective functions and  $f_1^*, f_2^*, \dots, f_k^*$  are the ideal value for the  $i^{th}$  objective. The largest deviation according to the increasing the  $p$  is dedicated. Moreover, the importance of this method can be justified by the detection of the proper value for  $r$ ; the value that fits the attitude of the decision-maker). According to the priority of expressed decision-makers, this method can generate only a single Pareto solution. In this study,  $r$  is chosen 1. Since the model proposed is strongly NP-hard a solving methodology, based on GA is adopted to resolve the model in the next section.

### Fuzzy Simulation

Since total measure costs  $TC(Q; \xi)$  is a fuzzy variable, it will be difficult to the expected value by using analytical methods. As a kind of Monte Carlo methods, fuzzy simulation (Selim and Ozkarahan, 2006) provides an effective approximation. The main steps of fuzzy simulation are given according to (Liu and Liu, 2009).

### Brief Description of Hunger Games Search (HGS) Optimization

The Hunger Games Search (HGS) is a new population-based model to deal with optimization problems based on social animals' characteristics in searching for food. Precisely, the algorithm hunger games search turns as follows: In each iteration, the Algorithm (HGS) searches near the optimal location, where the weights values, or the hunger values, represent the influence of hunger on the animal's individual activities. The adaptive and time-varying mechanisms allow to hunger games search algorithm the ability to deal with multi-modality and local optimal problems more efficaciously.

### Steps of Fuzzy simulation

- Step 1.** Set  $e = 0$ .
- Step 2.** Randomly generate  $\theta_k$  from the credibility space space  $(\theta; P; Cr)$ , write  $v_k = (2Cr\{\theta_k\}) \wedge 1$  and produce  $\xi(\theta_k)$ ,  $k = 1, 2, \dots, N$ , respectively. Equivalently, w randomly generate  $\xi(\theta_k)$  and write  $v_k = \mu(\xi(\theta_k))$  for  $k = 1, 2, \dots, N$ .
- Step 3.** Set two numbers:
  - a =  $TC(Q, \xi(\theta_1)) \wedge TC(Q, \xi(\theta_2)) \wedge \dots \wedge TC(Q, \xi(\theta_N))$
  - b =  $TC(Q, \xi(\theta_1)) \vee TC(Q, \xi(\theta_2)) \vee \dots \vee TC(Q, \xi(\theta_N))$
- Step 4.** Randomly generate  $r$  from  $[a, b]$ .
- Step 5.** If  $r \geq 0$ , then  $e = e + Cr\{TC(Q, \xi) \geq r\}$ .
- Step 6.** If  $r < 0$ , then  $e = e - Cr\{TC(Q, \xi) \leq r\}$ .
- Step 7.** Repeat the fourth to sixth steps for  $N$  times.
- Step 8.**  $TC = a \wedge 0 + b \vee 0 + e(b - a)/N$

### Approach Food

To express its approaching behaviors in mathematical formulas, the following formulas are proposed to imitate the contraction mode:

$$\overline{W}_1(t+1) = \begin{cases} \overline{X}(t) \cdot (1 + randn(1)), r_1 < l \\ \overline{W}_1 \cdot \overline{X}_b + R \cdot \overline{W}_2 \cdot [\overline{X}_b - \overline{X}(t)], r_1 > l, r_2 > E \\ \overline{W}_1 \cdot \overline{X}_b - R \cdot \overline{W}_2 \cdot [\overline{X}_b - \overline{X}(t)], r_1 > l, r_2 < E \end{cases} \quad (25)$$

where,  $\overline{R}$  is in the range of  $[-a, a]$ ;  $r_1$  and  $r_2$  respectively represent random numbers, which are in the range of  $[0, 1]$ ;  $randn(1)$  is a random number satisfying normal distribution;  $t$  indicates that the current iterations;  $\overline{W}_1$  and  $\overline{W}_2$  represent the weights of hunger;  $\overline{X}_b$  represents the location information of a random individual in all the optimal individuals;  $\overline{X}(t)$  represents each individual's location; and the value of 1 has been discussed in the parameter setting experiment.

The formula of  $E$  is as follows:

$$E = sech(|F(i) - BF|)$$

where,  $i \in 1, 2, \dots, n$ ,  $F(i)$  represents the fitness value of each individual; and  $BF$  is the best fitness obtained in the current iteration process.  $sech$  is a hyperbolic function ( $sech(x) = \frac{2}{e^x + e^{-x}}$ ).

The formula of  $\overline{R}$  is as follows:

$$\overline{R} = 2 \times a \times rand - a$$

where,  $rand$  is a random number in the range of  $[0, 1]$ ; and  $Max\_iter$  stands for the largest number of iterations.

### Hunger Role

The starvation characteristics of individuals in search are simulated mathematically.

The formula of  $\overline{W}_1$  in Eq. (5) is as follows:

$$\overline{W}_1(t) = \begin{cases} hungry(i) \cdot \frac{N}{SHungry} \times r_4, r_3 < l \\ 1 & r_3 > l \end{cases}$$

The formula of  $\overline{W}_2$  in Eq. (6) is shown as follows:

$$\overline{W}_2(t) = (1 - \exp(-|hungry(i) - SHungry|)) \times r_5 \times 2$$

where,  $hungry$  represents the hunger of each individual;  $N$  represents the number of individuals; and  $SHungry$  is

the sum of hungry feelings of all individuals, that is  $sum(hungry)$ .  $r_3$ ,  $r_4$  and  $r_5$  are random numbers in the range of  $[0, 1]$ .

The formula for  $hungry(i)$  is provided below:

$$hungry(i) = \begin{cases} 0, & AllFitness(i) = BF \\ hungry(i) + H, & AllFitness(i) \neq BF \end{cases}$$

where,  $AllFitness(i)$  preserves the fitness of each individual in the current iteration.

The formula for  $H$  can be seen as follows:

$$TH = \frac{F(i) - BF}{WF - BF} \times r_6 \times 2 \times (UB - LB)$$

$$H = \begin{cases} LH \times (1 + r), & TH < LH \\ TH, & TH \geq LH \end{cases}$$

Where:

- $r_6$ : Represents the random number in the range of  $[0, 1]$
- $F(i)$ : Represents the fitness value of each individual
- $BF$ : Represents the best fitness obtained in the current iteration process
- $WF$ : Represents the stands for the worst fitness obtained in the current iteration process
- $UB$  and  $LB$ : Indicates the upper and lower bounds of the search space, respectively
- $H$ : Represents the hunger sensation, is limited to a lower bound,  $LH$

### Brief Description of Chaotic Search

The chaos process is sensitive to the initial condition Schuster (2005). The nature chaos process is deterministic and quasi-random. So, the chaos process is apparently random and unpredictable. Mathematically, the chaos process is a randomness of a simple deterministic dynamical system. Then, the chaotic map can be defined as discrete-time of dynamical system running in a chaotic condition Alatas (2010):

$$x_{k+1} = f(x_k), 0 < x_k < 1, k = 0, 1, 2, \dots, N \quad (33)$$

where,  $\{x_k : 1, k = 0, 1, 2, \dots, N\}$  : Represents the chaotic sequence, which can be utilized as spread-spectrum sequence as random number sequence.

The chaotic sequences have been confirmed to be simple and fast produce; it is needless to store long sequences Heidari-Bateni and McGillem (1994). Only a few functions (chaotic maps) and parameters (initial conditions) are required even for very long sequences Alatas (2010). In this study,  $r$  chaotic variables are generated by the logistic mapping technique represented in Eq. 34; in this study we use the logistic map for four reasons:



- Firstly, the new position is found out by the logistic map and the jump over local optimum will not be repeated. So, the speed of convergence can be accelerated
- Secondly, the logistic map is simple and so very easy to implement
- Thirdly, the logistic map is easy to fix in every part of the *hunger games search* algorithm
- Fourthly, the complexity of the *hunger games search* algorithm will increase since chaotic map, provides every dimension, using another chaotic map:

$$z_i^{j+1} = \mu_i * z_i^j * (1 - z_i^j), i=1,2,\dots,r, j=1,2,\dots,N-1 \quad (34)$$

where,  $i$  is the serial number of chaotic variables and  $\mu_i = 4$ . Given the chaotic  $r$  variables and different initial values  $z_i^0 (i=1,2,\dots,r)$ , the values of the chaotic variables  $z_i^1 (i=1,2,\dots,r)$  are then produced by the logistic equation. Let,  $j = 1,2,\dots, N-1$  and hence, other  $N-1$  solutions are produced by the same method.

## The Proposed Methods CSHGS

### Solution Representation

When using hunger games search algorithm an importing task is how to convert the solution of a problem into agent code. It is necessary to analyze all application problems by combining the expression of the solution and the evolution operator that fits the problem. In the literature many encoding schemas are proposed Yu *et al.* (2006). In this study, the structure of problem's agent includes binary and integer variables which consist of six parts. The first part of agent indicates the procurement quantity between supplier and plant in period  $t$ . The second part is a binary which indicates if the production of product take place in plant or not in period  $t$ . The third part indicates the produced quantity in period  $t$ , while four and five part indicates the transported quantity between plants- DCs and DCs-Customers respectively. Finally, the six parts provides the incurred back-order quantity from product from customer in period  $t$ .

### Fitness Function

This study deals with the fitness function based on sequence.  $N_p$  agents of the population are arranged in descending order according to the values of the target function, which means the agents are arranged from good to bad. Suppose the parameter  $a \in (0;1)$  is given then the fitness function Liu and Liu (2009) based on sequence is:

$$fit(V_i) = a \times (1 - a)^{i-1}; i=1,2,\dots,N_p \quad (35)$$

where  $i = 1$  demonstrates that the agent is the best solution while  $i = N_p$  reveals the worst. As a result

the best agent does not exist in the last generation., the best agent marked  $V_0$  has to be reserved at the beginning calculation of iteration. If there is a better agent in the next generation then we use it to replace the former  $V_0$ . At the end of evolution, this agent can be considered as the solution of the model.

### Execution of Test Termination

The stop criterion is determined according to the parameter  $max\ gen$ . If  $iter < Maxgen$ , continue with Step 3 to Step 6 in the hybrid intelligence algorithm process. If  $iter > Max\ gen$ , stop the algorithm. The maximum fitness value and its corresponding individual of the population in the total iterative process are recorded.

---

### Algorithm 1: Pseudo-code of CSHGS

---

```

Initialize the parameters  $N, Max\_iter, l, D, SHungry$ ,
Initialize the positions of Individuals  $X_i (i = 1,2,\dots, N)$ 
While ( $t \geq Max\_iter$ ) do
    Calculate the fitness of all Individuals
    for (each portion  $\frac{Npop}{Fractoin}$  of worst of solutions)
    do Perform chaotic search for  $X_i$  to generate a
    new agent  $X'_i$  using Eq. (34)
     $X_i \leftarrow X'_i$ 
     $f_i \leftarrow f'_i$ 
    End for
    Update  $BF, WF, Xb, BI$ 
    Calculate the Hungry by Eq. (31)
    Calculate the  $W_1$  by Eq. (29)
    Calculate the  $W_2$  by Eq. (30)
    For (each portion  $3 * \frac{Npop}{Fractoin}$  of rest of solutions)
    do
        Calculate  $E$  by Eq. 26
        Update  $R$  by Eq. 27
        Update positions by Eq. 25
    End For
     $t = t + 1$ 
End While
Return  $BF, X_b$ 
    
```

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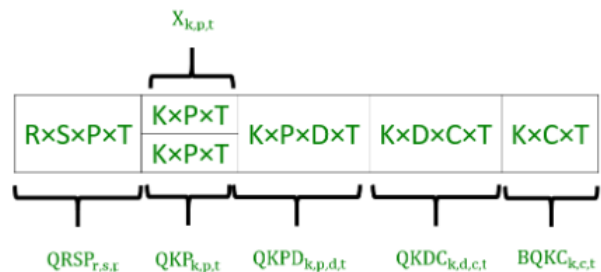


Fig. 2: The proposed agent structure



## Computational Results

In this study, the problem of integrating the procurement, production and distribution functions of a four-echelon supply chain network is presented, Table 1 shows the related random distribution for each parameter. In this study, we use the triangular fuzzy numbers to model imprecise parameters rather than others fuzzy distributions such as trapezoidal due to their simplicity and computational efficiency.

The fuzzy numbers  $\xi = (\xi^p, \xi^m, \xi^o)$ ; where,  $\xi^p$  is the most pessimistic,  $\xi^m$  is the most likely and  $\xi^o$  is most optimistic values. These values must be estimated for each fuzzy parameter.

**Table 1:** Model parameters

Deterministic parameters	
Parameter	Related random distribution
$\pi_k$	$\sim U(2,3)$
$\pi_r$	$\sim U(0.8,1.5)$
$PRcap_{r,p,t}$	$\sim U(10000,15000)$
$\alpha_{r,k}$	$\sim U(0.1,0.3)$
$PKcap_{p,t}$	$\sim U(40000,60000)$
$DKcap_{p,1}$	$\sim U(3500,4500)$
$T_{k,c,t}^{acc}$	$\sim U(600,900)$
$\beta_{k,c,t}$	$\sim U(0.10,1.15)$
Imprecise parameters	
Parameter	Related random distribution
$Scap_{r,s,t}$	$\sim U(1200,1200)$
$DC_{k,c,t}$	$\sim U(1000,2000)$
$\eta_{r,s,p,t}$	$\sim U(0.90,0.90)$
$BOC_{p,c,t}$	$\sim U(2,3)$
$CIRP_{v,p,t}$	$\sim U(1,2)$
$CIKD_{k,p,t}$	$\sim U(2,3)$
$CIKD_{k,d,t}$	$\sim U(4,5)$
$pt_{k,p,t}$	$\sim U(0.1,0.9)$
$st_{k,p,t}$	$\sim U(10,15)a$
$TT_{p,t}$	$\sim U(3000,4500)$
$CKP_{k,p,t}$	$\sim U(3,4)$
$CKS_{k,p,t}$	$\sim U(1,2)$
$TCSP_{r,s,p,t}$	$\sim U(1,2)$
$TCPD_{r,s,p,t}$	$\sim U(4,5)$
$TCDC_{r,s,p,t}$	$\sim U(2,3)$
$\lambda_{k,d,c,t}$	$\sim U(0.58,0.98)$

In doing so, the method proposed by Lai and Hwang (1993) is used. First, the most likely xim value for each imprecise parameter is specified randomly corresponding to the uniform distribution, the used values are illustrated in in Table 1. Then, the most pessimistic  $\xi^p$  and the most optimistic  $\xi^o$  values of a fuzzy number  $\xi$  are obtained as  $\xi^p = (1 - r_1) \xi^m$ ,  $\xi^o = (1 + r_2) \xi^m$  where  $(r_1, r_2)$  are two numbers randomly generated according to the uniform distribution [0.1,0.3]. The predetermined level is set to 0.8. The sizes of the designed test problems are given in Table 2.

The equivalent auxiliary crisp model is coded in GAMS 22.5/CPLEX 12.2 software and all experiments are computed using a Core i5 2.10 GHz computer with 16 GB RAM.

## Sensitivity and Robustness Analysis

It follows from Fig. 3 that the storage costs including (storage in plants and DCs) are equal to zero due to the fact of the favor of the distribution (distribution costs represent the highest value in the graph) rather than storage to satisfy the customer demand which verified by the very small backlog costs rather than production or distribution costs. In addition, we carried out the sensitivity analysis in order to investigate the impact of some input parameters affecting the both objective functions such as the capacity of supplier, the maximum of capacity of production. Table 3 represents the impact of on-time delivery provided by suppliers as well as the supplier capacity on values of the second objective. It follows from Fig. 4 that the quantities of raw materials delivered on time increase as both parameters increase. A decision is to consider the highest weight to these criteria when selecting suppliers.

In all benchmarks, we use Standard Deviation (STD) and the Average (AVE) to compare all metaheuristics. The using of these two measures demonstrate the ability of algorithms to avoid local minima. The Table 4 demonstrate that the average objective values found by HGS and CSHGS over perform the ones obtained by the GA and PSO in different instances. The convergence curve of the different metaheuristic in optimizing problem instance 1, 3 and 6 are given in Fig. 5-9. The instances are divided in two types of problems as small size and large size. In the small size, to ensure the integrity and accuracy of the model, their results are obtained by programming mathematical model in GAMS software. Table 3 demonstrates an objective function value for each problem with various indicators and parameters in small size. In the large size, four test problems are examined that show the results of the proposed method compared with the well-known methods such GA, PSO and the standard HGS. These comparisons are calculated based on the deviation of the current value and best value found so far. Tables 4-5 shows computational results which involve combined objective function in the small and large sizes. Moreover, the convergence performance is given of all algorithms of some instances.

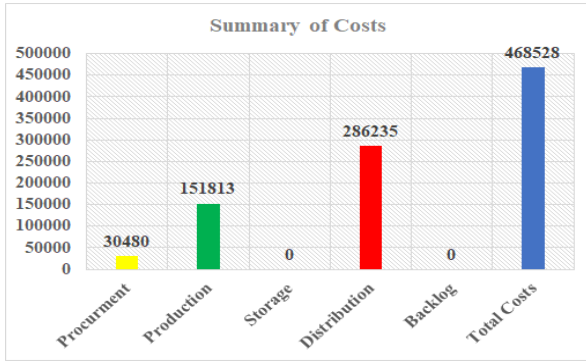


Fig. 3: Summary of costs

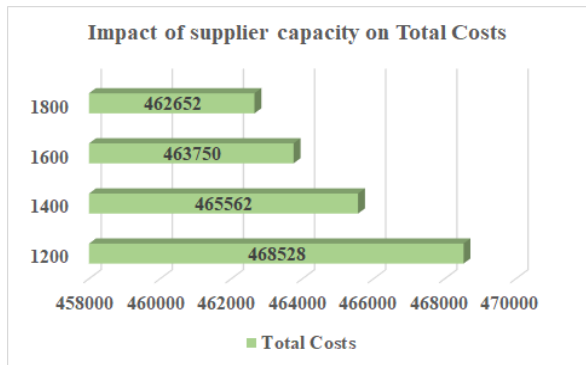


Fig. 4: Sensitivity analysis of supplier capacity on Total Cost

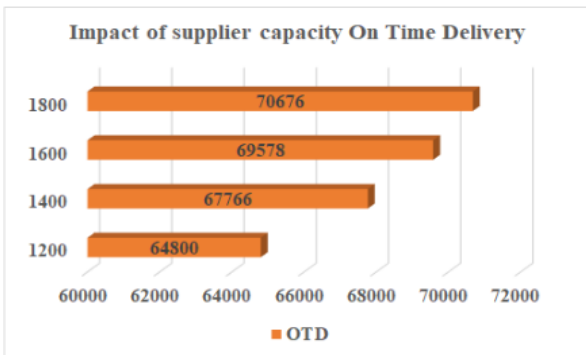


Fig. 5: Sensitivity analysis of supplier capacity on time delivery

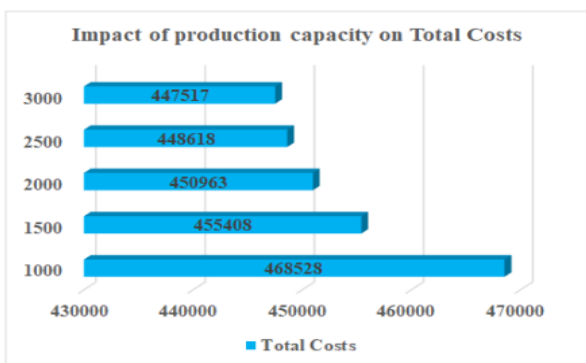


Fig. 6: Sensitivity analysis of production capacity on total cost

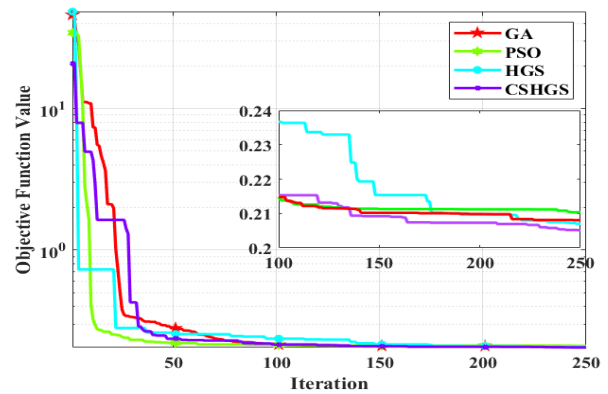


Fig. 7: Convergence curves of the algorithms for instance 1

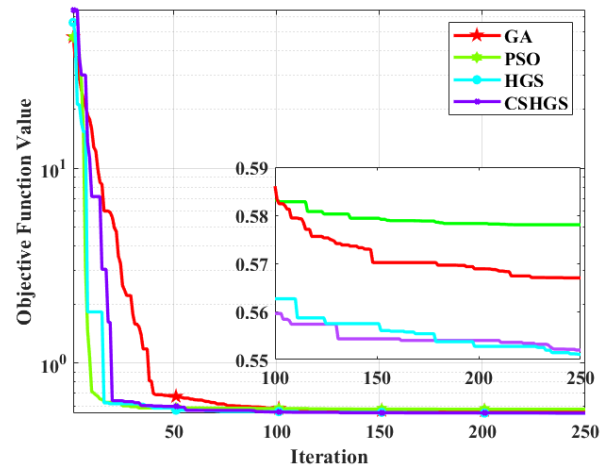


Fig. 8: Convergence curves of the algorithms for instance 2

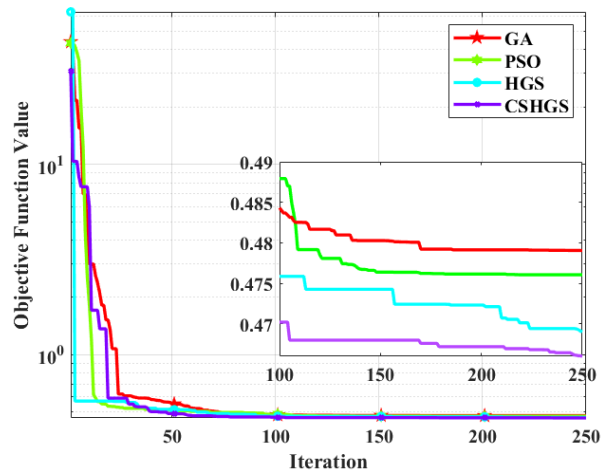


Fig. 9: Convergence curves of the algorithms for instance 3

**Table 2:** Instance's problem

Instance	No. of raw material	No. of supplier	No. of plant	No. of DCs	No. of customers	No. of products	No. of period
Instance 1	2	3	2	3	2	2	10
Instance 2	4	5	4	5	4	3	10
Instance 3	6	7	6	7	6	6	10
Instance 4	8	9	8	9	8	8	10
Instance 5	10	11	10	11	10	10	10
Instance 6	12	13	12	13	12	12	10

**Table 3:** Sensitivity analysis of supplier capacity and on-time delivery rate impact - Instance 1

Delivery rate	On-time			
	1200	1400	1600	1800
0,4	141606	162466	182501	202354
0,5	177008	203083	228126	252942
0,6	212410	243700	273751	303531
0,7	247811	284317	319377	354120
0,8	283213	324933	365002	404708
0,9	318615	365550	410627	455297

**Table 4:** Computational results

	GAMS	GA	PSO	HGS	CSHGS
Instance 1	0,204	0,208	0,210	0,207	0,205
Instance 2	0,224	0,235	0,232	0,228	0,225
Instance 3	*	0,479	0,476	0,469	0,466
Instance 4	*	0,423	0,435	0,421	0,422
Instance 5	*	0,612	0,611	0,608	0,603
Instance 6	*	0,567	0,578	0,551	0,552

**Table 5:** Computational results

	GA		PSO		HGS		CSHGS	
	TC	ODT	TC	ODT	TC	ODT	TC	ODT
Instance 1	565982	78278	566919	78408	565513	78214	564576	78084
Instance 2	1171544	227401	1168699	226848	1164904	226112	1162058	225559
Instance 3	2106043	525543	2101771	524477	2091803	521990	2087531	520924
Instance 4	5749098	988275	5797579	996609	5741018	986886	5745058	987580
Instance 5	8450995	1412779	8445753	1411903	8430025	1409274	8403812	1404892
Instance 6	9944379	1966750	10014187	1980556	9842841	1946668	9849188	1947923

**Table 6:** Quantity of inventory of raw materials in plant

		t1	t2	t3	t4	t5	t6	t7
rm1	p1	2439.28	2439.28	-	5555.31	3521	1212.26	8283.28
	p2	6366.3	16682.74	16682.74	18704.67	17610.12	14477.4	22729.87
	p3	-	187.82	-	-	-	-	-
	p4	-	1790.27	-	415.92	-	-	1535.15
	p5	2707.41	2411.17	2411.17	-	-	-	4589.89
	p6	-	-	-	-	-	-	2917.77
	p7	715.54	715.54	-	-	-	-	-
	p8	1025.53	1025.53	-	-	-	-	-
rm2	p1	-	-	14150.6	11642.42	10404.4	9024.39	7857.62
	p2	4530.41	4530.41	5304.28	4794.79	3498.96	1939.05	-
	p3	-	1144.14	921.78	921.78	921.78	921.78	921.78
	p4	1897.87	1897.87	691.34	492.4	-	1473.47	-
	p5	16358.52	16057.67	16057.67	15144.63	15144.63	15144.63	14438.6
	p6	-	-	17046.69	25808.07	25808.07	25808.07	25808.07
	p7	-	427.7	-	-	830.48	1953.21	-

**Table 6:** Continue

rm3	p1	5280.78	5280.78	3738	1415.12	-	13288.79	11871.6
	p2	-	-	5814.77	5195.93	4021.18	1930.77	-
	p3	-	201.58	-	-	-	-	-
	p4	16225.33	16225.33	15308.07	15066.44	28901.78	36149.96	33826.65
	p5	-	2552.88	2552.88	1113.23	1113.23	1113.23	-
	p6	-	-	-	-	-	5206.74	5206.74
	p8	-	21452.67	20352	20352	20352	28472.98	31699.54
	p1	2424.94	2424.94	-	1761.21	-	1569.39	-
rm4	p2	6623.23	6623.23	6623.23	5937.93	4956.3	3069.07	-
	p3	-	27195.47	27027.02	27027.02	27027.02	46524.77	54795.49
	p4	2857.4	2857.4	640.59	373.01	-	-	-
	p5	1116.53	871.65	871.65	-	-	15616.44	14942.42
	p7	-	-	23021.4	43432.25	52537.81	51304.51	48677.32
	p8	-	-	-	-	17162.76	17162.76	17162.76
	p1	3344.7	3344.7	2020.79	2131.61	1111.63	-	-
	p2	-	-	-	1361.38	-	-	-
rm5	p3	-	233.61	-	-	-	-	-
	p4	-	-	-	517.31	-	-	-
	p5	324.53	-	-	-	-	-	-
	p6	3322.43	-	-	-	-	-	-
	p7	-	-	738.59	738.59	738.59	-	411.07

**Table 7:** Quantity of inventory of finished products in plants

Height		t1	t2	t4	t5	t6	t7
k1	p1	3615,786	-	-	-	-	-
	p2	-	-	-	-	-	9512,191
	p1	1094,351	-	1735,122	5971,797	14547,404	14706,776
k2	p2	-	-	2556,559	-	-	-
	p3	1063,525	-	-	-	-	-
	p4	1219,026	-	-	-	-	-
	p7	-	-	-	-	4372,894	16510,461
k3	p2	2315,674	2315,674	-	-	-	-
	p4	-	-	-	-	-	13446,979
	p5	-	-	1286,509	-	-	-
k4	p6	-	6614,733	-	-	-	-
	p2	-	-	-	6523,538	5204,306	5204,306

**Table 8:** Quantity of inventory of finished products in DCs

Height		t1	t2	t4	t5	t6	t7
k1	p1	3615,786	-	-	-	-	-
	p2	-	-	-	-	-	9512,191
	p1	1094,351	-	1735,122	5971,797	14547,404	14706,776
k2	p2	-	-	2556,559	-	-	-
	p3	1063,525	-	-	-	-	-
	p4	1219,026	-	-	-	-	-
	p7	-	-	-	4372,894	16510,461	-
k3	p2	2315,674	2315,674	-	-	-	-
	p4	-	-	-	-	-	13446,979
	p5	-	-	1286,509	-	-	-
k4	p6	-	6614,733	-	-	-	-
	p2	-	-	-	6523,538	5204,306	5204,306

As it is represented, the GA and PSO get stuck into local optimal solutions after a while iteration, respectively while the CSHGS explore the space search in early iteration and can reach convergence in later iterations with

the best identified result 0.208. Consequently, the solution of the CSHGS outperforms the other algorithms in search quality and uniform over iterations. The optimal solutions are presented in Table 6-8.

## Conclusion

This study devoted the integration problem of procurement, production and distribution in supply chain network under uncertainty within the credibility framework. The model proposed in this study is a bi-objective mixed-integer linear programming. This model considers technological constraints issuing a lot of supply chain network in world that aims to minimize the total costs such as production, storage and distribution as well as maximize the on-time deliveries to ensure a continuous flow of production and minimize line stoppages in plants due to unavailability of raw materials items.. To model the problem which is similar to the real planning problems, the objective function coefficients (e.g., procurement cost, production cost and inventory holding) and other parameters (e.g., demand and production capacity). The proposed model combines the expected value model and chance-constrained model. To transform the bi-objective model to single objective model the *Lp-metric* is used. To solve the proposed model for largest instances, we address a hybrid algorithm based on a recent metaheuristic called Hunger Game Search (HGS). This algorithm employs the so-called chaotic search to prevent premature convergence and entrapment in local optima. The numerical results showing the efficiency of the proposed solution. The proposed model considered the fuzziness as the source of uncertainty. However, future studies should aim to address hybrid uncertainties, such as an encounter with fuzziness and roughness. For instance, it is broadly accepted the representation of demands a triangular fuzzy number (a, b, c) variable from the view point of the fuzzy theory, but the values of a, b and c may emerge within complete or uncertain information. In a sense, the values of a, b and c are of rough characteristics. Thus, the decision-makers have to manage the fuzzy number of rough parameters by adapting the clients demand in order to be fitly defined as a fuzzy rough variable Liu and Liu (2002).

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## Author's Contributions

**Kaoutar Douaioui:** Conceptualization, formal analyzes, development, original draft and Investigation.

**Mouhsene Fri:** Conceptualization, publication, review and editing.

**Charif Mabrouki:** review, methodology, editing, supervision and validation.

**El Alami Semma:** supervision and final approval

## Ethics

The authors verify that the research paper is original and has unpublished data. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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