RAIRO-Oper. Res. 52 (2018) 473–497
https://doi.org/10.1051/ro/2017076

RAIRO Operations Research
www.rairo-ro.org

HYBRID IMPROVED CUCKOO SEARCH ALGORITHM AND GENETIC ALGORITHM FOR SOLVING MARKOV-MODULATED DEMAND

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Abstract. One of the fundamental problems in supply chain management is to design the effective inventory control policies for models with stochastic demands because efficient inventory management can both maintain a high customers' service level and reduce unnecessary over and under-stock expenses which are significant key factors of profit or loss of an organization. In this study, a new formulation of an inventory system is analyzed under discrete Markov-modulated demand. We employ simulation-based optimization that combines simulated annealing pattern search and ranking selection (SAPS&RS) methods to approximate near-optimal solutions of this problem. After determining the values of demand, we employ novel approach to achieve minimum cost of total SCM (Supply Chain Management) network. In our proposed approach, hybrid improved cuckoo search algorithm (ICS) and genetic algorithm (GA) are presented as main platform to solve this problem. The computational results demonstrate the effectiveness and applicability of the proposed approach.

Mathematics Subject Classification. 90B05, 91B74

Received August 21, 2017. Accepted October 13, 2017.

1. Introduction

The problem of production-inventory planning is one of the important issues of Operations Research and Management Science problems that have received a considerable amount of attention of industrial engineers, practitioners, managers as well as the business researchers. In fact, supply chain management has been noticed as an approach to enhance the efficiency of the material and information flows among different organizations [41, 42]. Consequently, complexity of managing and handling the networks is increasing exponentially over time and many inventory control models are appeared to cope with various aspects. Generally speaking, there are two models in inventory control problem. Firstly, according to the work of Sethi and Thompson [60], it is assumed in a deterministic inventory system that the values of the state variables can be measured and are unchanged over

Keywords and phrases: Improved cuckoo search algorithm, genetic algorithm, Markov chain Monte Carlo procedure, stochastic demand, inventory control.

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time. Quite often, the value of a state variable can be directly measured but clear or fixed determination of states may not occur in practice. As a matter of fact, the stochastic statement of the production planning and inventory control model is more realistic than deterministic statement. On the other hand, in the stochastic optimal control theory, the condition of the system is described and supervised by stochastic processes. Therefore, the concept of time is closely involved in the state of the system and it is delineated as a stochastic differential equation [3]. Also, it is stated in the model of Diaz *et al.* [20] that managers widely employ supply chain management tools to manage resources successfully and product in order to gain maximum supply chain surpluses and minimize the risks involved in the systems. Therefore, it is a fundamental problem of SCM to design inventory control policies in which stochastic demands [30] should be considered. It seems that stochastic control problem is a fairly simple concept of prompting a stochastic process in one or more aspects.

The present paper focuses on the classical stochastic inventory control problem with uncertain demands. Hence, we consider a new approach based on Cuckoo search and Monte Carlo simulation to analyze inventory control problem because we focus on the classes of costs those are considered as main parameters of current expenses in this area. In the framework of this study, stochastic optimal control is well suited for addressing many general problems including inventory control problems. This is becoming an essential attention of mangers to consider dynamic and stochastic forecasting of the parameters involved in the problems. So, turbulences in markets eventually lead to demand uncertainties which have a substantial impact on performance of SCM. In this context, firms focus on their ability to control costs and make profits. These demand uncertainties may have influence in some situations, and it would be more realistic than simple deterministic analysis. As long as uncertain demands continuously change over time, plan of supply chain of assets or commodities frequently reveals high degrees of severity. So, one of the main challenging issues in fluctuating demand is to find out the optimal solutions or strategies of the given problem. The evolutions in many different aspects in this context are to be considered and it is highly useful to have a substantial framework for future study. The proposed model presents a hybrid algorithm to solve the problem. To be more meticulous, we just develop a model based on stochastic demand of the customers. Furthermore, we consider the situations in practice where the customer demand is stochastic and the on hand inventories of parts or finished-goods are uncertain. However, a hybrid algorithm consists of a cuckoo search algorithm for inventory control optimization and a method to evaluate different solutions in the evolution optimization process are presented in this article.

The rest of this paper is organized as follows. In Section 2, a brief literature review of Markov-modulated demand and stochastic inventory model is presented. The problem formulation comes in Section 3 after defining the parameters and the variables. In Section 4, a hybrid algorithm is proposed to solve and analyze the problem. The solution method is investigated in Section 5 by a numerical example. Finally, the conclusion is made in Section 6.

2. Literature review

The correlated demand has been modeled in different stochastic models, and it has been considered as one of the main issue in supply chain management. A multiproduct monopoly business faces several demand classes with random and correlated demands. Several authors study similar systems and derived heuristics and mathematical model to solve this class of problems. Diaz and Ezell [19] employ auto-regressive (AR) to describe auto-correlated demand in a lost sale stochastic inventory model. Diaz and Bailey [18] consider auto-correlated demands in stochastic inventory models involving lost sale. Zhang *et al.* [66] develop a model to make it more relevant to trading with the inventory replenishment problem for multiple associated products. They consider the replenishment problem with complete backordering and correlated demand and hence a simulation based optimization approach is used to solve this complex problem. Shaikh *et al.* [57] proposed an inventory model with backlogging for deteriorating items with interval-valued inventory costs and stock-dependent demand under inflationary conditions. Recently, Diaz *et al.* [20] describe an inventory system in which condition to correlated demand is frequently determined in competitive markets where the control review system is periodic. In their study, the demand for products is considered as a discrete Markov-modulated demand where a probability distribution is used in order to determine product quantities of the same items. According to the model of Hausman and Erkip [28], cross correlated demands are two types of dependent components those are recognized in some consumers' demands. Markov-modulated structures are studied by several authors with different characteristics of different demand classes. Some of those relevant studies are being mentioned here. For instance, Cheng and Sethi [15] investigate optimality of state-dependent policies in lost sales inventory models whose demand is represented by Markov-modulated demand. Another one is Cheng and Song [14] who analyze a multistage serial inventory system subject to a Markov-modulated demand. Presman and Sethi [45] discuss a stochastic continuous review inventory model where the demand process is made up of a continuous part and a compound Poisson process. They show that the (s: minimum stock level, S: maximum stock level) newsvendor policy is optimal by using an appropriate potential function. This function is then shown to satisfy the dynamic programming associated with the problem. Muharremoglu and Tsitsiklis [37] focus on Markov modulated demand and Markov modulated stochastic lead times, and demonstrate that state dependent echelon base stock policies in capacitated serial inventory systems are optimal. Also, Benkherouf and Johnson [6] examine the stochastic continuous review inventory model for single item with a fixed ordering cost where the demand is driven by a special type of a piecewise Markov deterministic process. Alshamrani [3] consider a stochastic optimal control of an inventory model with a deterministic rate of deteriorating items. He presents an inventory model using perturbation by a Wiener process and he also uses Hamilton–Jacobi–Bellman principle to solve a nonlinear partial differential equation (PDE). Betts [8] develops a hybrid simulation model to minimize cost target level for a single item, single-stage production-inventory system in which an analytical approximation of the inventory is derived and the short fall distribution is used to calculate demands via simulation. The author emphasizes on optimal policy which is an echelon base-stock policy with state dependent order-up-to levels and suggests some algorithms to determine the optimal levels of stocks. In stochastic inventory literature, the works of DasRoy *et al.* [17], Pal *et al.* [39, 40], Roy *et al.* [48]. Sana [49–52], Sana *et al.* [53] and Sarkar *et al.* [54–56] should be mentioned among others.

On the other hand, mathematical programming especially Mixed Integer Linear Programming (MILP) has become one of the most widely explored methods for process scheduling problems because of its rigorousness, flexibility and extensive modeling capability. Fleischmann *et al.* [24] consider the integration of forward and reverse distribution, and suggest a generic integer programming formulation. Schultmann *et al.* [59] develop a hybrid method to establish a closed-loop supply chain for spent batteries. Their model includes a two stage facility location optimization problem in order to minimize total cost of the system. The authors implement the model in GAMS and solve it using a branch-and-bound algorithm. Similarly, Beamon and Fernandes [5] focus on closed loop supply chain and address a network model where the plants produce new products and remanufacture the used products. A multi-period integer programming model is introduced to determine what warehouses and collection centers should be opened, and what should have the sorting capabilities and how much would be shipped among the sites. Min *et al.* [36] present a nonlinear integer program to solve the multi-echelon, multi commodity closed loop network design problem involving product returns. However, their models do not consider temporal consolidation issues in a multiple planning horizon. Kannan *et al.* [32] develop a multi echelon, multi period, multi-product closed loop supply chain network model for product return and the decisions are made regarding all items in the network such as material procurement, production, distribution, recycling and disposal. They suggest a heuristic based genetic algorithm (GA) in order to solve mixed integer linear programming model. Eventually, these results achieved by GA are compared with the solutions achieved through GAMS optimization software. The solution shows that the developed methodology executes excellently in connection with running time and quality of solutions.

Our proposed model considers a stochastic demand in which fixed and variable cost networks, shortage costs are changing over time and it is stated that the cost of inventories is dependent on time periods. The objective cost function is minimized based on a novel heuristic approach called Cuckoo Search Algorithm (CS). Furthermore, the main effects and sensitive analyses of parameters of this model are investigated. In this work, like the model of Bertazzi *et al.* [7], the stochastic inventory problem involves a single-item whose replenishment takes place over the next business day and not as a perpetual inventory review policy. The contribution of the existing literature is given in Table 1 as follows:

TABLE 1. Contribution of previous literature.

Authors' names	Optimization techniques	Field of application
Abdulrani *et al.* [1]	Cuckoo search algorithm	Side lobe uppression in antenna array
Abu-Srhan and Daoud [2]	Hybrid algorithm	Travelling salesman problem
Alshamrani [3]	Hamilton–Jacobi–Bellman principle	Inventory model
Asadzadeh [4]	Genetic algorithm	Job shop scheduling
Beamon and Fernandes [5]	A sensitivity analysis	Closed loop supply chain
Benkherouf and Johnson [6]	Quasi-variational inequalities (QVI)	Inventory model
Bertazzi *et al.* [7]	Matheuristic approach, stochastic dynamic programming	Inventory Routing Problem, transportation services
Betts [8]	Hybrid simulation model	Inventory, constrained production
Bhandari *et al.* [9]	Cuckoo search algorithm, wind driven optimization	Satellite image segmentation
Cárdenas-Barrón [10]	Adaptive genetic algorithm	Lotsizing problem
Cárdenas-Barrón and Taleizadeh [11]	Hybrid metaheuristics algorithms	Inventory management
Cárdenas-Barrón *et al.* [12]	Calculus technique	Replenishment lot size problem, rework, EPQ
Çelebi [13]	Genetic algorithm	Inventory control
Chen and Song [14]	Markov-modulated	Inventory models
Cheng and Sethi [15]	Markov-modulated	Inventory models
Civiciolu [16]	Backtracking Search Optimization	Numerical optimization
DasRoy *et al.* [17]	Calculus technique	Production, inventory, rework, stochastic demand
Diaz and Bailey [18]	Simulated annealing	Inventory models
Diaz and Ezell [19]	Auto-regressive (AR)	Inventory model
Diaz *et al.* [20]	Simulated annealing, pattern search (PS) & ranking and selection (RS)	Periodic stochastic inventory
Dorigo *et al.* [21]	Ant colony optimization	Traveling salesman problem
Fan and Liang [22]	Hybrid of GA and PSO	Nelder-Mead simplex search
Fan and Zahara [23]	Hybrid simplex search and PSO	Unconstrained optimization
Fleischmann *et al.* [24]	Hybrid method	Closed-loop supply
Formato [5]	Metaheuristic	Applied electromagnetics
Gandomi and Alavi [26]	Krill herd	Area of optimization
Geem *et al.* [27]	Harmony search	Traveling salesman problem
Hausman and Erkip [28]	Markov-modulated	Multi-echelon inventory systems
He *et al.* [29]	Group search optimizer inspired by animal behavior	Train artificial neural networks

(continued...)

Table 1. Continued.

Authors' names	Optimization techniques	Field of application
Hurley *et al.* [30]	Heuristics	Stochastic Inventory Control Models
Husseinzadeh [31]	Optics inspired optimization	Engineering design application
Kannan *et al.* [32]	Genetic algorithm (GA)	Closed loop supply chain model
Kennedy and Eberhard [33]	Particle Swarm Optimization (PSO)	Social behavior
Kuo and Han [34]	Hybridization of GA and PSO	Supply chain model
Mantegna [35]	Mantegna's algorithm	Levy stable stochastic processes
Min *et al.* [36]	A Lagrangian relaxation heuristic	Multi-echelon, multi commodity closed loop network
Muharremoglu and Tsitsiklis [37]	Markov modulated	Multi-echelon Inventory Systems
Natarajan *et al.* [38]	Cuckoo search	Spam filtering
Pal *et al.* [39]	Calculus technique	Stochastic demand, product recovery, inventory
Pal *et al.* [40]	Calculus technique	Newsvender inventory, distribution-free case
Panda [41]	Calculus technique	Coordination of two-echelon supply chains
Panda [42]	Calculus technique	Coordination of a socially responsible supply chain
Passino [43]	Bacterial foraging	Distributed optimization and control
Pfeifera *et al.* [44]	Genetic algorithm	Quantifying the risk of project delays
Presman and Sethi [45]	Calculus technique	Inventory model
Rao and NareshBabu [46]	Cuckoo search	Optimal power flow
Rinott [47]	Derivation of inequalities	Probability of correct selection
Roy *et al.* [48]	Calculus technique	Uncertain demand, three-layer supply chain
Sana [49, 50]	Calculus technique	EOQ, random sales price, stochastic demand
Sana [51]	Calculus technique	EOQ, stochastic demand, own and rented warehouse
Sana [52]	Calculus technique	Sales teams' initiative, stochastic demand, reorder point, production lotsize, two-stage supply chain
Sana *et al.* [53]	Bi-level programming, Shapley value model	Supply chain of COCOA
Sarkar *et al.* [54]	Calculus technique	EPQ, stochastic demand, imperfect production
Sarkar *et al.* [55]	Calculus technique	Distribution free case, continuous review inventory, service level constaints
Sarkar *et al.* [56]	Calculus technique	Distribution free case, consignment policy, retailer's royalty reduction
Shaikh *et al.* [57]	PSO	Two-warehouse inventory model
Santosa *et al.* [58]	GA	Multi-product inventory

(continued...)

TABLE 1. Continued.

Authors' names	Optimization techniques	Field of application
Schultmann *et al.* [59]	Hybrid method	Closed-loop supply chain
Sethi and Thompson [60]	Optimal control theory	Management and economic modelling
Simon [61]	Biogeography-based optimization (BBO)	Optimization problems
Tofighi *et al.* [62]	Humanitarian logistics network	Mixed uncertainty problem
Tsoukalas and Fragiadakis [63]	Multivariable linear regression, genetic algorithm	Prediction of occupational risk
Valian *et al.* [64]	Improved cuckoo search	Neural network training
Yang and Deb [65]	Cuckoo search, Levy flights stochastic process	Optimization problems
Zhang *et al.* [66]	A heuristic approach	Joint replenishment problem (JRP)
Our present article	Hybrid improved cuckoo search algorithm and genetic algorithm	Stochastic inventory problem

3. Model definition

The proposed model has four stages presented in Figure 1. In this model, uncertain demands are converted to deterministic values via SAPSR&S method. Main mathematical model of this study is defined in deterministic mode (vide Sect. 3.2) so that an optimal solution would be obtained from deterministic model by applying metaheuristic approaches. In the following subsections, main stages of this conceptual model are defined as follows (Fig. 1).

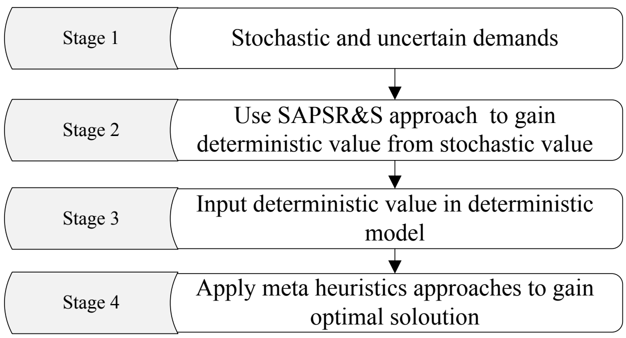

FIGURE 1. Conceptual model of this study.

3.1. Discrete Markov chain Monte Carlo procedure

There are many Markov Chain Monte Carlo procedures in the literature. We perform a simulation based optimization that combines simulated annealing (SA), pattern search (PS), and ranking and selection (R&S) that is proposed in the work. Therefore, we focus on discrete Markov Chain Monte Carlo with four main steps. In this procedure, correlated demands are given via probability distribution p_{ij}, *i.e.*, probability mass function. Firstly, the heuristics for the Discrete Markov Chain Monte Carlo procedure is introduced as follows. Here, we consider the following parameters to develop the model.

i	Iteration
r	Period of planned horizon
x_i	Accepted state (accepted candidate solution)
y	Nominated state (proposed candidate solution)
$H(x_i)$	Objective cost function evaluating state x_i
T	Temperature
α	Acceptance function
χ	Decision space
$\chi_{\min}$	A small region in decision spacefor objective function value,
r_1	Maximum temperature
l_k	Stage length k_{th} stage
Z	Accepted candidate solution for specific x_i value
δ	Step length
h	A constant that depends on the number of alternatives
A	Number of alternatives
p_{ij}	Transition probability
$1-\theta$	Desired confidence level
n_0	Initial number of replications
N_i	Additional replications
s_i^2	Sample variance of the n_0 observations
d^*	Significant difference specified by the user
IZ	Indifference zone

Various steps involved in the proposed SAPSR&S heuristics are outlined as follows:

(A) $i=1$ and $k=1$

(B) Assign an initial state x_0, and $\hat{f}_{\min}=f(x_0)$

(C) Repeat:

SA:

1. while $k \leq r$:
2. while $i \leq l_k$:
3. Randomly sample y from the given distribution
4. Randomly sample U from $U(0,1)$
5. $ifU \leq \min\left\{1, e^{\frac{[f(y)-f(x_i-1)]}{\tau_k}}\right\}, x_i = y$

PS:

6. Deterministically generate n additional neighbors (test points) to x using step length δ
7. Simulate and obtain$\hat{f}(y)$ per potential neighbor

R&S:

8. Select y such that the performance of y is no more than 5% greater than the performance of$x$
9. Determine the sample variance s_i^2 of the n_0 observations
10. Check the number of observations n_0 to be independent and normally distributed.
11. Determine additional replications N_i per test point.
12. Execute additional replications per each competing alternative
13. Select the best y
14. $if\hat{f}_{\min} > f(x_i), \hat{f}_{\min} =, Z = H(x_i)$
15. $i = i+1,$

16. $k = k + 1$,
17. $\tau_k = \alpha\tau_{k-1}$, until termination criteria is satisfied or $k > r$

(D) $(H_{\min}, Z)$ is the estimated solution, where $H_{\min}$ is the minimum cost value and Z is the candidate solution.

We use number of additional replications N_i that is calculated based on formula developed by Rinott [47] as follows:

$$N_i = \max\left\{n_0 + 1, \left[\left(\frac{h}{d^*}\right)^2 S_i^2\right]\right\} \tag{3.1}$$

According to main constraints coming from the model shown in subsection 3.2, an initial candidate solution is created. Then, Discrete Markov Chain Monte Carlo procedure is performed to generate demands. In order to evaluate total cost, the following procedure is applied accordingly. First of all, a random number between 0 and 1 obtained from uniform distribution is created to estimate the probabilistic displacement. The procedure will perform local neighborhood systemically for a candidate solution that is accepted and new pair of solutions is generated. Each pair is selected if their costs are no more than 5% greater than the original. In such iteration, solutions whose costs are above the original, the original policy is accepted. Besides it, each new policy is accepted by additional replications. Summarily, new replications are performed for each pair that report lower costs. If original costs are above the acquired costs then reported lower cost policy is selected, otherwise original policy is accepted. This process is continued until stop criteria is achieved.

3.2. Formulation of the problem

In this subsection, first the fundamental assumptions of the problem are reviewed. Then, the list of input parameters and decision variables are introduced. Finally, the mathematical formulation is constructed in a step by step manner. The most important assumptions and input parameters and variables of the problem are as follows:

- shortage is allowed. Consequently, the cost of shortage is applied;
- the model is considered for finite time horizon;
- there is just one product;
- cost parameters are some non-stochastic deterministic values;
- the period demand of the customer is stochastic and uncertain;
- the time taken for transporting the product between the levels is homogeneous and not taken into consideration.

Indices:

i	Index for suppliers; $i \in I$
j	Index for retailers; $j \in J$
k	Index for customers; $k \in K$
t	Index for time periods; $t \in T$

Input parameters:

a_{ijt}	Fixed cost of sending goods from supplier i to retailer j at time t.
b_{ijt}	Variable cost of sending one goods from supplier i to retailer j at time t.
f_{jkt}	Fixed cost of sending goods from retailer j to customer k at time t.
g_{jkt}	Variable cost of sending one goods from retailer j to customer k at time t.

h_{jt}	Fixed cost of inventory level of retailer j at time t.
ch_{jt}	Variable cost of inventory level of retailer j at time t.
c_{sjt}	Cost of stock-out of retailer j at time t per finished-goods.
D_{kt}	Stochastic demand of customer k at time t.
U_j	Maximum inventory level of retailer j.
C_{ijt}	transportation procurement capacity of sending goods from supplier i to retailer j at time t.
Decision variables:	
γ_{ijt}	A binary variable equal to 1 if the quantity of sending goods from supplier i to retailer j at time t is greater than zero, otherwise 0.
δ_{jkt}	A binary variable equal to 1 if the quantity of sending goods from retailer j to customer k at time t is greater than zero, otherwise 0.
α_{jt}	A binary variable equal to 1 if the quantity of inventory level of retailer j at time t is greater than zero, otherwise 0.
β_{jt}	A binary variable equal to 1 if the level of stock-out of retailer j at time t is greater than zero, otherwise 0.
s_{ijt}	A non-negative variable representing the quantity sent from supplier i to retailer j at time t.
r_{jkt}	A non-negative variable representing the quantity sent from retailer j to customer k at time t.
$\acute{I}_{jt}$	A non-negative variable representing the quantity level of retailer j at time t.
y_{jt}	A non-negative variable representing the shortage level of retailer j at time t.

We provide the mathematical formulation of the periodic-review deterministic inventory problem and explain some of the notation used throughout the paper. Each retailer $j \in J$ defines a maximum inventory level U_j and has a given starting inventory level $\acute{I}_{jt} \leq U_j$, where $\acute{I}_{jt}$ and U_j are integer values and inventory level at each period t would not greater than U_j. Each retailer j has to satisfy the demand of customer k at time t, r_{jkt} is defined on the basis of a stationary random variable D_{kt}. The probability distribution of D_{kt} is discrete and obtained from Discrete Markov Chain Monte Carlo procedure described in previous section. If j is visited at time t, then the quantity shipped to j at time t is such that the inventory level of j reaches its maximum value U_j. When the level of the inventory is negative, the excess demand is not backlogged. In this situation, the initial inventory level at the successive time period is set equal to zero. The inventory level of the supplier at time t is equal to the inventory level at time $(t-1)$ plus the total quantity sent to retailer j from all suppliers at time $(t-1)$ and minus the quantity shipped to the all customers from retailer j at time $(t-1)$. So, the level of the inventory is given by minimum between $\acute{I}_{jt-1} + \sum_{i \in I}(s_{ijt-1})\gamma_{ijt-1} - \sum_{k \in K}(r_{jkt-1})\delta_{jkt-1}$ and maximum inventory level (U_j). Also, it is assumed that the inventory level at time t cannot be negative. Consequently, according to previous explanation, inventory level of retailer j at time t is formulated as follows:

$$\acute{I}_{jt} = \max\left(0, \min\left(U_j, \acute{I}_{jt-1} + \sum_{i \in I}(s_{ijt-1})\gamma_{ijt-1} - \sum_{k \in K}(r_{jkt-1})\delta_{jkt-1}\right)\right), \ j \in J, \ t \in T \tag{3.2}$$

For each time $t \in T$, the inventory level $\acute{I}_{jt}$ cannot be negative. If the inventory level of retailer j at time t is positive, fixed cost (h_{jt}) is charged and variable cost (ch_{jt}) is calculated per goods. While total demands of customers are not satisfied, a penalty is charged if it is negative and it is calculated based on Cost of stock-out of retailer. The supplier has an initial integer inventory level $\acute{I}_{jt}$.The problem is to determine, for each time period $t \in T$, the subset of retailers to serve in order to minimize the sum of the expected inventory cost at the retailers, penalty cost for stock-out at the retailers and transportation cost over the planning horizon. The deterministic version of the problem can be formulated as follows:

$$\text{Min} TC = TU + TD + TI \tag{3.3}$$

The total cost of the suppliers, including procurement and transportation costs for sending the goods to the retailers, is

$$TU = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} a_{ijt}\gamma_{ijt} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} b_{ijt}s_{ijt}, \tag{3.4}$$

The cost of the retailers including procurement and transportation costs for sending the goods to the customers is

$$TD = \sum_{j\in J}\sum_{k\in K}\sum_{t\in T} f_{jkt}\delta_{jkt} + \sum_{j\in J}\sum_{k\in K}\sum_{t\in T} g_{jkt}r_{jkt}, \tag{3.5}$$

The cost of holding inventory and shortages at the retailers is

$$TI = \sum_{j\in J}\sum_{t\in T} h_{jt}\alpha_{jt} + \sum_{j\in J}\sum_{t\in T} \acute{I}_{jt}ch_{jt} + \sum_{j\in J}\sum_{t\in T} y_{jt}cs_{jt}\beta_{jt}, \tag{3.6}$$

The inventory level of jth retailer at time t is

$$\acute{I}_{jt} = \text{Max}\left(0, \min\left(U_j, \acute{I}_{jt-1} + \sum_{i\in I}(s_{ijt-1})\gamma_{ijt-1} - \sum_{k\in K}(r_{jkt-1})\delta_{jkt-1}\right)\right), \; j \in J, \; t \in T \tag{3.7}$$

The difference of inventory and shortage levels of jth retailer at time t is

$$\acute{I}_{jt} - y_{jt} = \acute{I}_{jt-1} + \sum_{i\in I}(s_{ijt-1})\gamma_{ijt-1} - \sum_{k\in K}(r_{jkt-1})\delta_{jkt-1}, \; j \in J, \; t \in T \tag{3.8}$$

The limitations of variables with parameters of the whole chain are as follows

$$\acute{I}_{jt} \le U_j\alpha_{jt}, \; j \in J, \; t \in T \tag{3.9}$$
$$y_{jt} \le U_j\beta_{jt}, \; j \in J, \; t \in T \tag{3.10}$$
$$\alpha_{jt} + \beta_{jt} \le 1, \; j \in J, \; t \in T \tag{3.11}$$
$$s_{ijt} \ge U_j\gamma_{ijt} - \acute{I}_{jt}, \; i \in I, j \in J, \; t \in T \tag{3.12}$$
$$s_{ijt} \le U_j - \acute{I}_{jt}, \; i \in I, j \in J, \; t \in T \tag{3.13}$$
$$s_{ijt} \le U_j\gamma_{ijt}, \; i \in I, j \in J, \; t \in T \tag{3.14}$$
$$r_{jkt} \le U_j\delta_{jkt}, \; j \in J, \; k \in K, \; t \in T \tag{3.15}$$
$$r_{jkt} \le \acute{I}_{jt}, \; j \in J \;, k \in K, \; t \in T \tag{3.16}$$
$$\sum_{i\in I} s_{ijt} \le \acute{I}_{jt}, \; j \in J, \; t \in T \tag{3.17}$$

$$\sum_{i \in I} s_{ijt} \leq C_{ijt},\ j \in J,\ t \in T \tag{3.18}$$

$$s_{ijt} \geq 0,\ i \in I,\ j \in J,\ t \in T \tag{3.19}$$

$$r_{jkt} \geq 0,\ j \in J,\ k \in K,\ t \in T \tag{3.20}$$

$$\gamma_{ijt} \in \{0,1\},\ i \in I,\ j \in J,\ t \in T \tag{3.21}$$

$$\delta_{ijt} \in \{0,1\},\ i \in I,\ j \in J,\ t \in T \tag{3.22}$$

$$\alpha_{jkt} \in \{0,1\},\ j \in J,\ k \in K,\ t \in T \tag{3.23}$$

$$\beta_{jkt} \in \{0,1\},\ j \in J,\ k \in K,\ t \in T \tag{3.24}$$

The objective function (3.3) expresses the minimization of the total cost, given by the sum of three terms: total upstream supply chain cost (3.4), total downstream supply chain cost (3.5), and total inventory cost (3.6) include the inventory cost at the retailers and the penalty cost due to the stock-out at the retailers. As we mentioned before, constraints (3.7) define the inventory level at the retailers. Constraints (3.8) define the inventory and the stock-out level at the retailers. Constraints (3.9)–(3.11) ensure that, for each retailer $j \in J$ at each time period $t \in T$, either a positive inventory level α_{it} not greater than the maximum inventory level U_j is permitted or a stock-out quantity β_{it} not greater than U_j is permitted. The constraints (3.12)–(3.14) represent the order-up-to level constraints and guarantee that the quantity s_{ijt} shipped to each retailer j at each time $t \in T$ is either $\left(U_j - \acute{I}_{jt}\right)$ if i is served at time t, otherwise 0. As the demand is not backlogged, the quantity $\left(U_j - \acute{I}_{jt}\right)$ always allows reaching the order-up-to level when the retailer is served. The constraints (3.15) represent the level constraints and guarantee that the quantity r_{jkt} shipped to each retailer j at each time $t \in T$ is either $U_j \delta_{jkt}$ if customer k is served by retailer j at time t, otherwise 0.The constrain (3.16) shows that the quantity r_{jkt} is less than equal to $\acute{I}_{jt}$. Constraints (3.17) guarantee that the total quantity sent to the retailers at each time $t \in T$ is not greater than the quantity available at the supplier. Constraints (3.18) are the transportation capacity constraints. Finally, constraints (3.19)–(3.24) define the decision variable of the system.

4. Improved cuckoo search genetic algorithm

In this section, all approaches used to analyze the proposed problem are described. Cuckoo Search (CS) algorithm will be presented in the first subsection, then how CS algorithm performance can improve via successfully manipulation is detailed. Finally, GA and Improved Cuckoo Search Genetic Algorithm (ICSGA) are cited at the end of this section.

4.1. Cuckoo search algorithm

In recent years, in the literature, numerous works on this topic have been presented based on swarm algorithms. These algorithms include the biological evolutionary processes, such as: genetic algorithm (GA) [10, 58], Hybrid Metaheuristics Algorithms [11, 12], Particle Swarm Optimization Algorithm (PSO) [33] and Harmony Search (HS) [27], Bacterial Foraging Optimization Algorithm (BFOA) [43], Artificial Bee Colony Algorithm (ABC), Central Force Optimization Algorithm (CFO) [25], Group Search Optimizer (GSO) [29], Krill Herd Algorithm (KH) [26], Optics Inspired Optimization (OIO) [31], Biogeography Based Optimization (BBO) [61], Ant Colony Optimization (ACO) [21] and Backtracking Search Optimization (BSO) [16].

Cuckoo Search Algorithm (CS) has been introduced by Yang and Deb [65] based on the Leìvy flight behavior and brood parasitic behavior. In many scientific literatures, the CS algorithm has been elegantly demonstrated to provide excellent performance in optimization: power flow [46], Symmetric Linear Antenna Array [1], Neural Network Training [64], Image Segmentation [9] and other optimization [38]. The main idea of the algorithm is based on breeding behavior such as brood parasitism of some species.

Similar to other evolutionary methods, CS also starts with an initial population. New solutions $x^{(t+1)}$ are generated for a cuckoo$i$; a *Lévy* flight is performed using the following equation:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \bigotimes Lévy(\lambda) \tag{4.1}$$

where $\alpha(\alpha > 0)$ represents a step size. To determine step size, we should pay attention to the scales of problem. The *Lévy* flight is a random walk with the random step size which follows the following *Lévy* distribution.

$$Lévy\,(\lambda) \sim u = t^{-\lambda},\ (1 \leq \lambda \leq 3) \tag{4.2}$$

There are a few ways for generation of steps of the *Lévy* flights, but one of the most efficient and yet straight forward way is to use the so-called Mantegna [35] algorithm for a symmetric *Lévy* stable distribution. Here 'symmetric' means that the steps can be positive and negative. In an algorithm proposed by Mantegna [35], the step lengths can be calculated by

$$S = \frac{u}{|v|^{1/\beta}} \tag{4.3}$$

where $\beta(0 < \beta \leq 2)$ is an index, and u and v are stochastic variables drawn from normal distributions as follows:

$$u \sim N\left(0, \sigma_u^2\right),\ v \sim N\left(0, \sigma_v^2\right), \tag{4.4}$$

$$\sigma_u = \left[\frac{\Gamma\,(1+\beta)\,sin\frac{\pi\beta}{2}}{\Gamma\left(\frac{1+\beta}{2}\right)\beta.2^{(\beta-1)/2}}\right]^{1/\beta}, \sigma_v = 1 \tag{4.5}$$

Finally, Gamma function ($\Gamma\,(x)$) is calculated by

$$\Gamma(x) = \int_0^\infty t^{z-1} e^{-t} dt \tag{4.6}$$

Concisely, CS is a population based algorithm in which initial population is randomly generated within the limits of the control parameter. Then, the *Lévy* flight operator is applied on all individuals until a stopping criterion is reached.

4.2. Improved cuckoo search algorithm

Improved Cuckoo Search Algorithm is inspired in the work of Valian *et al.* [64]. There are two important factors in cuckoo search. These parameters perform as fixed value in traditional version of cuckoo search and are introduced in order to find globally and locally improved solutions. The first parameter is p_a which is very important to fine-tuning of solution vectors, and can be possibly used in fitting convergence rate of algorithm. The second parameter, λ, is the step size related to the scales of problem. If these parameters are not tuned well, the performance of the algorithm would be poor and may be gone to increase in number of iterations or lost best solution.

In order to solve potential problem aroused from traditional version of algorithm, we perform Improved Cuckoo Search which is focus on these parameters (p_a and λ). The most significant difference between the ICS and CS is in the way of tuning p_a and λ . Fixed value parameters (p_a and λ) of CS algorithm lead to drawbacks in computing best solution. Therefore, to improve the performance of the CS algorithm and eliminate difficulties related to tuning p_a and λ, the ICS algorithm uses variables p_a and λ. To achieve a better fine-tuning of solution

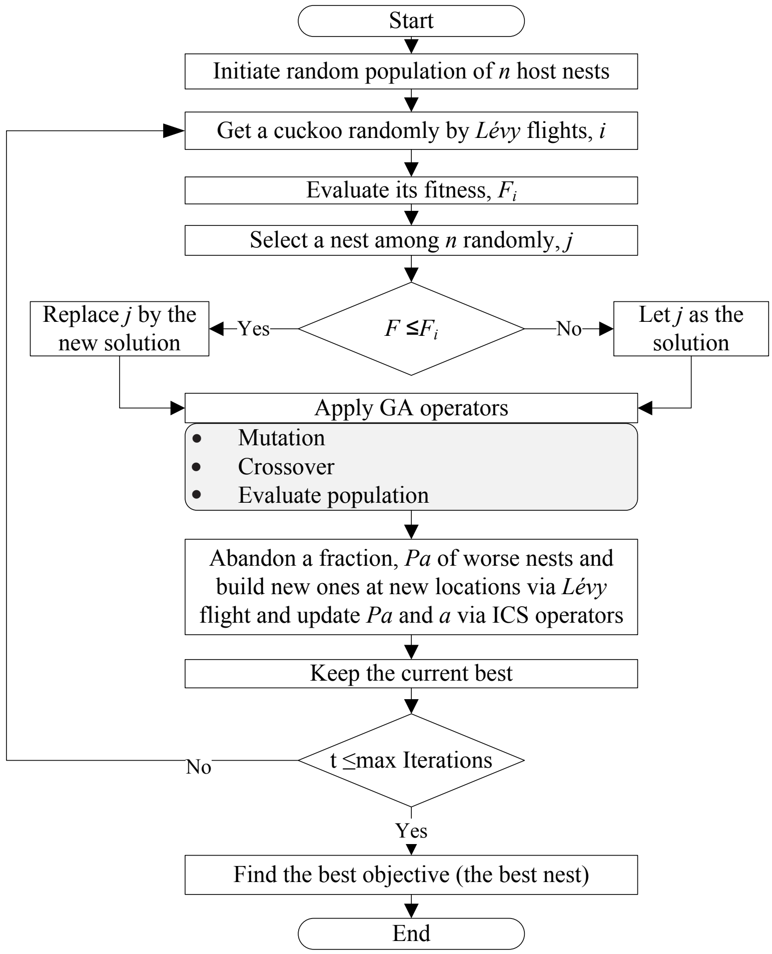

FIGURE 2. Proposed approach flowchart.

vectors, the values of p_a and λ should be dynamically changed with the number of iteration and decreased them from high value to low value. Therefore, we use equations (4.7)–(4.9) as ICS operators, where NI and gn denote the number of total iterations and the current iteration respectively [64].

$$P_a\left(gn\right) = P_{a_{\max}} - \frac{gn}{NI}\left(P_{a_{\max}} - P_{a_{\min}}\right) \tag{4.7}$$

$$\alpha\left(gn\right) = \alpha_{\max} \exp\left(c.gn\right) \tag{4.8}$$

$$c = \frac{1}{NI} ln\left(\frac{\alpha_{\min}}{\alpha_{\max}}\right) \tag{4.9}$$

4.3. Genetic algorithm

The genetic algorithm (GA) is a stochastic global search technique that solves problems by imitating processes observed during natural evolution [34]. The procedure of GA is a simulation following behavior of biological evolution. GA not only adopts the spirit of creature elimination rule but also finds the approximate optimal solution after the process of coding, decoding and constant operation (reproduction, crossover and selection). GA is performed in many applications by scholars like Humanitarian Logistics Network Design [62], Job Shop Scheduling [4], Prediction [63], Inventory Control [13] and Risk of Project [44]. Crossover and mutation are introduced as main GA operators. In the next subsection, we shall describe how to apply these operators in ICS to achieve better performance.

4.4. Hybrid of ICS and GA

Due to each own merits in searching, there already have been many researches working on integrating meta-heuristic algorithms. GA, known as most famous evolutionary algorithm, has been applied with other meta-heuristics in order to improve solution procedure. Mostly, GA has been performed with PSO. For example, Fan and Liang [22] integrate Nelder–Mead simplex search method (NM) with GA and PSO. Fan and Zahara [23] introduce GA into calculation process of PSO and calculate its adaptive value, and compare the value with single GA and PSO. Kuo and Han [34] extend an efficient method based on hybrid of GA and PSO. There are many studies which introduce hybrid GA with other algorithms, but it is rarely considered hybrid of GA with CS in the existing literature. Idea of hybrid GA with CS is developed by Abu-Srhan and Daoud [2]. Our suggested algorithm in this study combines the advantages of GA and ICS and overcomes the main disadvantage of GA easily becoming trapped in the local minima through the ICS. So, the main steps of proposed approach are introduced as follows (see Fig. 2 above).

In order to demonstrate and evaluate the performance of the proposed hybrid intelligent algorithm and to validate the results obtained from ICSGA; existing algorithms of CS, ICS and GA are employed as well.

5. Numerical test

In this section, we present some numerical examples to illustrate the effective range of analytical results of previous section. We present the numerical solution of the stochastic inventory control and particular values of the parameters. The specific input variables integrated in the simulation model are specified in Table 2. In this table, three levels of input data of stochastic inventory model, the SAPSR&S algorithm and employed algorithms with numeric information are processed and output data is generated.

This example is selected in a manner to demonstrate the capability of the proposed method. In addition, the performances of the proposed methods (ICSGA) are compared with GA, CS and ICS. So, the following data shown in Tables 3 and 4 and parameters are used to justify the stochastic inventory model.

- number of supplier of finished goods = 3;
- number of retailer = 2;
- number of customer = 4;
- number of time periods = 10;

The algorithms mentioned above are implemented in Mat lab 2014, Mac OS edition and run on a computer whose processor is Intel Core i5 1.6 GHz, with 4GB main memory, 250GB hard disk. As we mentioned before (Tab. 2) the performances of all methods have been compared, while the number of runs is set at 100 for all methods. According to Figures 3–6, total cost (TC) value is obtained in each proposed method.

The levels of both inventories are illustrated in Figures 7–10 given by different algorithms. We conclude that inventory levels given by the algorithms go to maximum level during time periods and total pattern of them are not significantly different.

To determine objective of this study, we perform four algorithms. Figures 11–13 show the performance of each algorithm based on different types of cost: total downstream supply chain cost (TD), total upstream supply chain cost (TU), and total inventory cost (TI). In the convergence paths of TU and TI, GA has the best performance than others, but in compare with ICSGA, this gap is not significantly promising. In other hand, in the convergence paths of TD, GA has the worst performance, while ICS provides the best result.

Table 2. Input type description.

(1) Inventory model	(1.1) Demand distribution: discrete demand modeled as Markov Chain (1.2) Costs: (1.2.1) Fixed Costs (1.2.2) Variable Costs (1.2.3) Shortage (1.3) Maximum inventory level allowed in the system(Uj=70)
(2) SAPSR&S algorithm	(2.1) SA (2.1.1) Maximum temperature (based in acceptance =98%) (2.1.2) Temperature Gradient $\tau_k = 0.85\tau_{k-1}$ (2.1.3) Length of the stage (20,000 periods) (2.1.4) Stopping criteria (combination of (s, S)±10%, average costs ±5%, and $\tau_i<$ 100 units) (2.2) Pattern search (2.2.1) Step Size $\delta\pm$ 15% (2.2.2) Number of neighbors to explore per iteration = 11 (2.3) Ranking and selection (2.3.1) Indifference zone value 5% (2.3.2) h based on the indifference value and the number of neighbor to explore 3.619 (2.3.3) Initial number of replications $n0= 2$
(3) Employed algorithms (CS, ICS, GA and ICSGA)	(3.1) Common parameters (3.1.1) Number of population (nests) =40 (3.1.2) Number of Iterations =100 (3.2) CS, ICS and ICSGA (3.2.1) β= 1.5 (3.2.1) α=1 (3.3) GA and ICSGA (3.3.1) Crossover probability=0.7 (3.3.2) Mutation probability=0.03 (3.4) ICSGA and ICS (3.4.1) $P_{a_{\max}} = 1$ (3.4.2) $P_{a_{\min}} = 0$ (3.5) CS (3.5.1) Pa=0.3

Finally, according to Figures 3–6, proposed approach (ICSGA) achieves the best result and introduces as the best algorithm in this study.

The corresponding solutions are tabulated in Table 5. It reveals that the result of using GA is not better than the hybrid method in TC and TU. Among the other three methods, ICS has the smallest cost in TU. Additionally, total rank is gained from total score computed by average rank of algorithm in different costs (TU, TD, TI and TC). It is resulted that total score of ICSGA has minimum value, so it will be selected as the best approach in this study. Regarding Table 5 and the converging paths shown in Figures 3–6, GA has better performance than ICS and CS, so second place goes to this algorithm.

TABLE 3. Fixed cost and variable costs of the model.

	Fixed cost													
	f_{ijt}						v_{jkt}							
	$j=1$			$j=2$			$k=1$		$k=2$		$k=3$		$k=4$	
	$i=1$	$i=2$	$i=3$	$i=1$	$i=2$	$i=3$	$j=1$	$j=2$	$j=1$	$j=2$	$j=1$	$j=2$	$j=1$	$j=2$
$t=2$	31	27	26	38	21	33	31	33	29	21	23	28	29	39
$t=3$	38	24	32	37	32	28	38	31	27	31	32	34	38	26
$t=4$	34	28	25	25	29	37	25	35	36	31	25	34	28	34
$t=5$	23	30	37	32	34	35	26	30	33	38	20	29	36	29
$t=6$	27	22	40	20	34	40	22	40	36	30	35	20	28	37
$t=7$	29	32	35	28	33	31	39	24	39	28	25	26	36	36
$t=8$	40	24	27	26	20	26	33	22	40	34	29	28	35	23
$t=9$	23	28	32	23	21	22	30	22	24	35	34	25	27	38
$t=10$	37	32	22	23	26	32	33	21	22	30	27	24	24	40

	Variable cost													
	a_{ijt}						b_{jkt}							
	$j=1$			$j=2$			$k=1$		$k=2$		$k=3$		$k=4$	
	$i=1$	$i=2$	$i=3$	$i=1$	$i=2$	$i=3$	$j=1$	$j=2$	$j=1$	$j=2$	$j=1$	$j=2$	$j=1$	$j=2$
$t=1$	5	5	8	6	7	7	5	2	2	9	7	2	6	9
$t=2$	8	1	6	9	6	6	6	2	5	1	1	1	8	5
$t=3$	6	2	9	5	3	9	1	1	8	1	8	9	4	7
$t=4$	2	2	7	5	6	6	6	6	8	2	9	3	5	9
$t=5$	2	7	6	8	1	1	4	3	3	2	9	3	1	3
$t=6$	4	5	8	3	6	2	1	5	2	6	8	3	2	4
$t=7$	7	2	8	5	6	8	5	7	6	6	8	5	6	5
$t=8$	8	5	9	9	7	5	2	5	6	1	5	6	3	7
$t=9$	8	2	1	6	9	8	2	5	4	9	2	1	9	8
$t=10$	3	1	8	8	9	2	2	5	2	7	4	8	2	1

TABLE 4. Costs of retailers.

	H		co		Cs	
	$j=1$	$j=2$	$j=1$	$j=2$	$j=1$	$j=2$
$t=1$	10	11	2	7	69	49
$t=2$	14	11	8	6	68	61
$t=3$	13	15	2	10	41	60
$t=4$	12	10	2	7	62	56
$t=5$	15	12	6	9	48	61
$t=6$	13	11	2	6	53	60
$t=7$	13	15	9	5	56	45
$t=8$	15	14	9	9	69	43
$t=9$	14	13	8	2	52	70
$t=10$	13	12	3	3	70	45

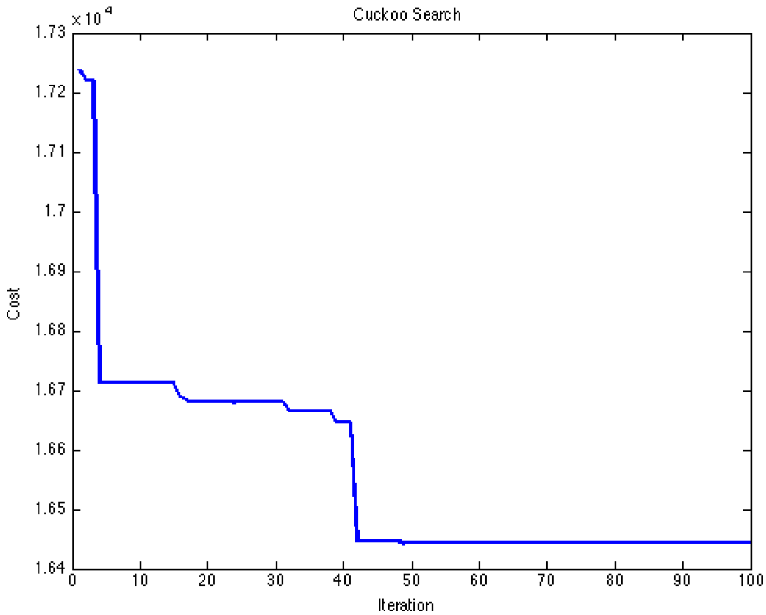

FIGURE 3. The convergence paths of TC given by CS.

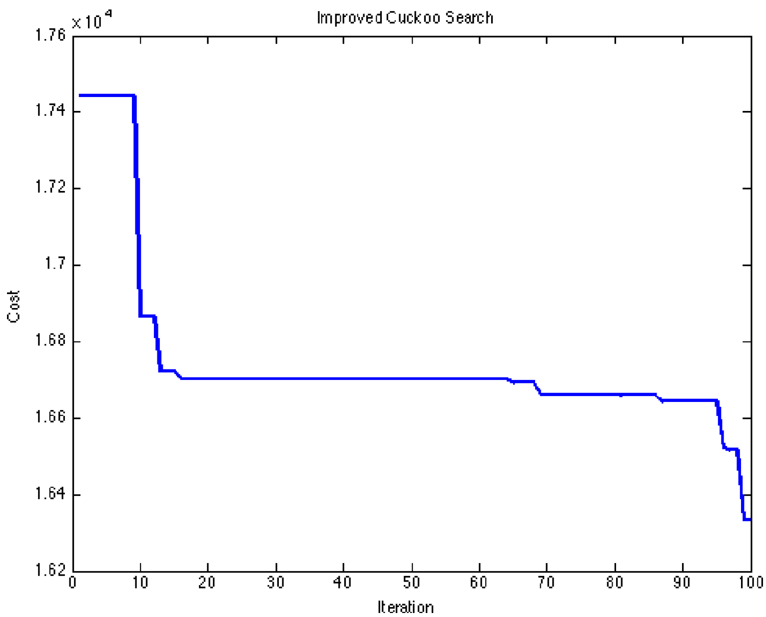

FIGURE 4. The convergence paths of TC given by ICS.

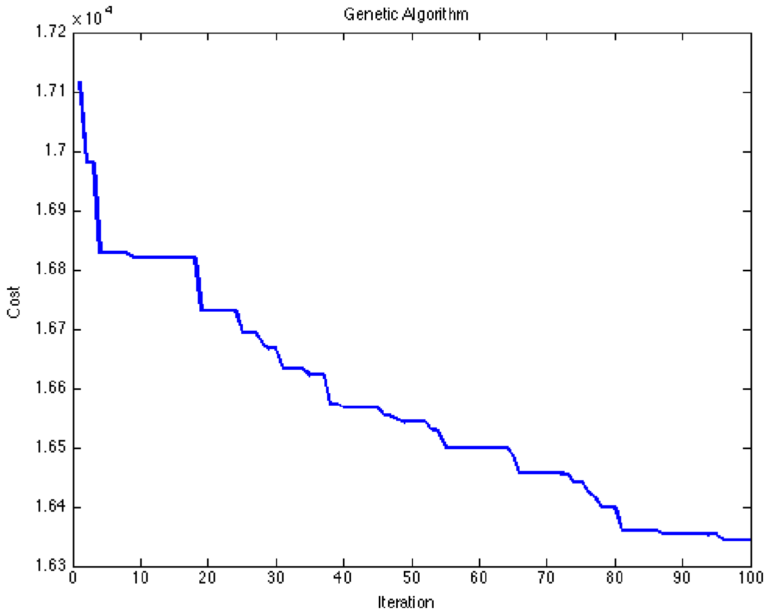

FIGURE 5. The convergence paths of TC given by GA.

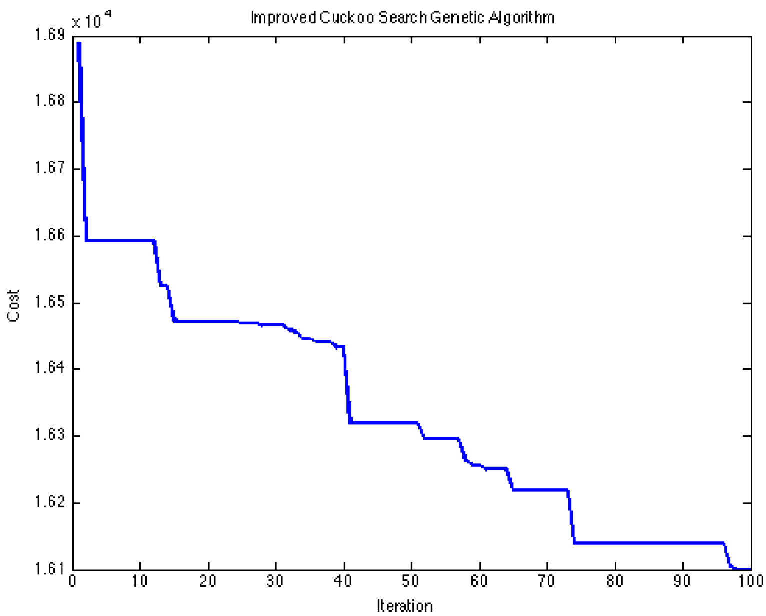

FIGURE 6. The convergence paths of TC given by ICSGA.

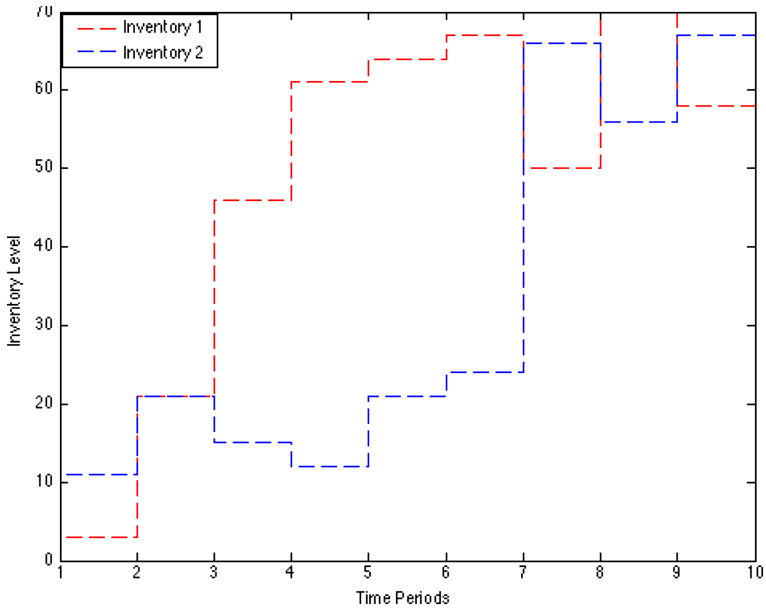

FIGURE 7. Inventory level given by CS.

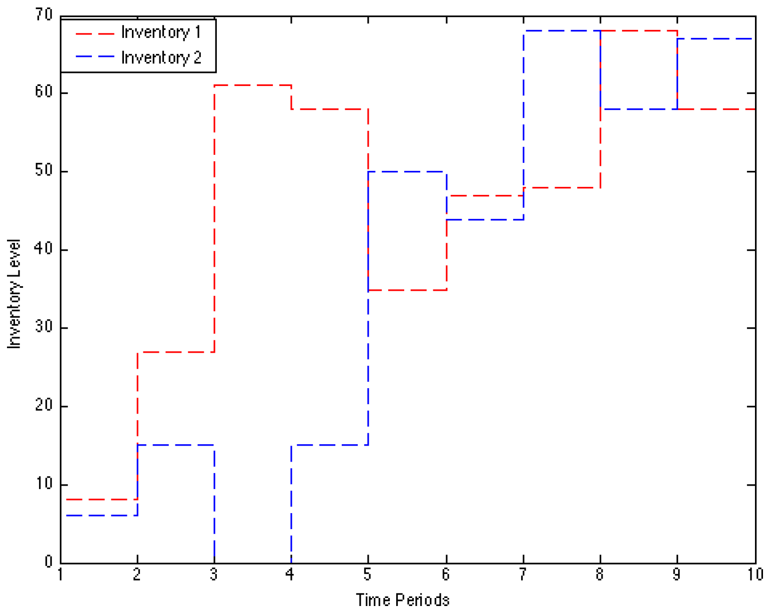

FIGURE 8. Inventory level given by ICS.

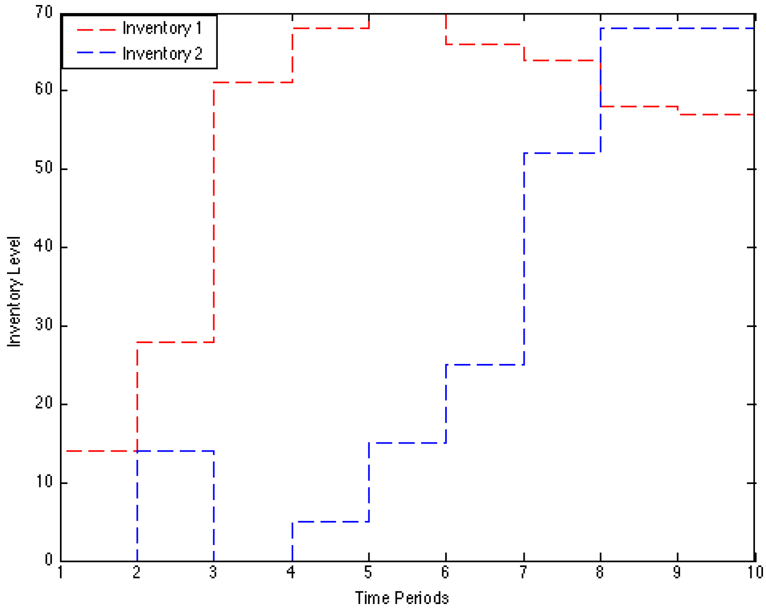

FIGURE 9. Inventory level given by GA.

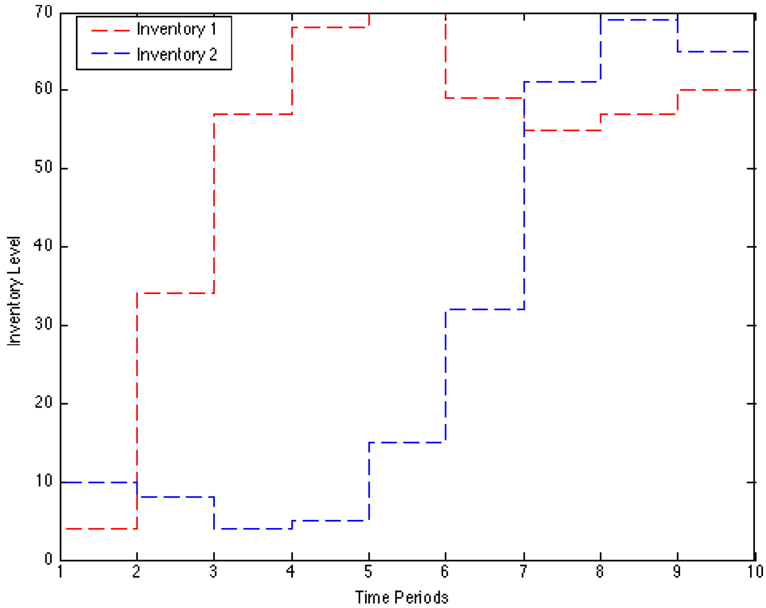

FIGURE 10. Inventory level given by ICSGA.

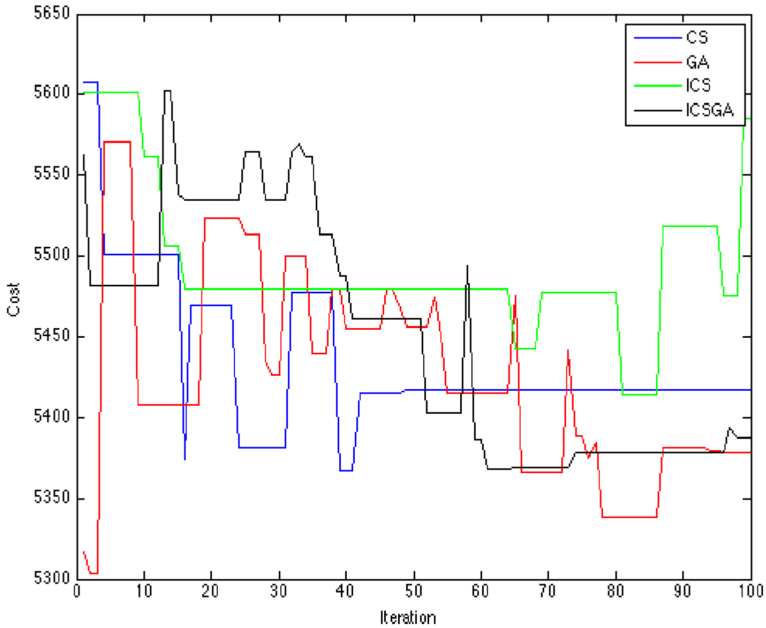

FIGURE 11. The convergence paths of TU based on algorithms.

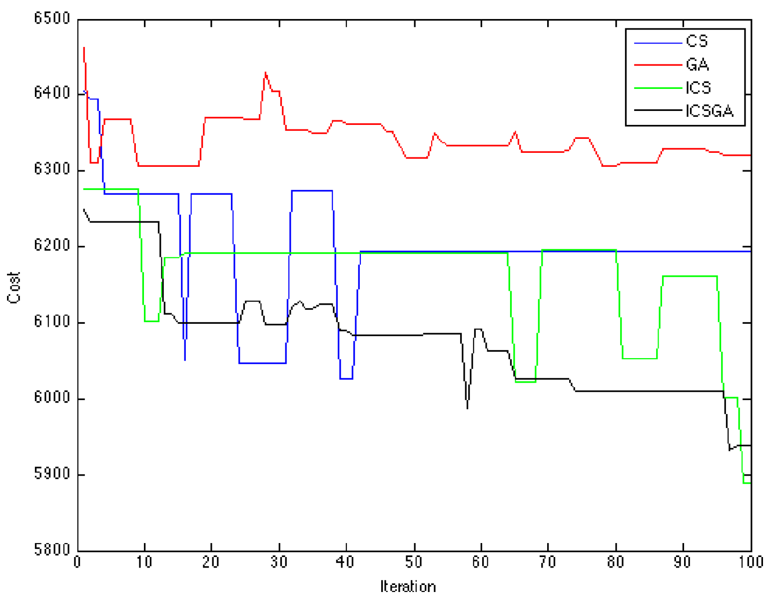

FIGURE 12. The convergence paths of TD based on algorithms.

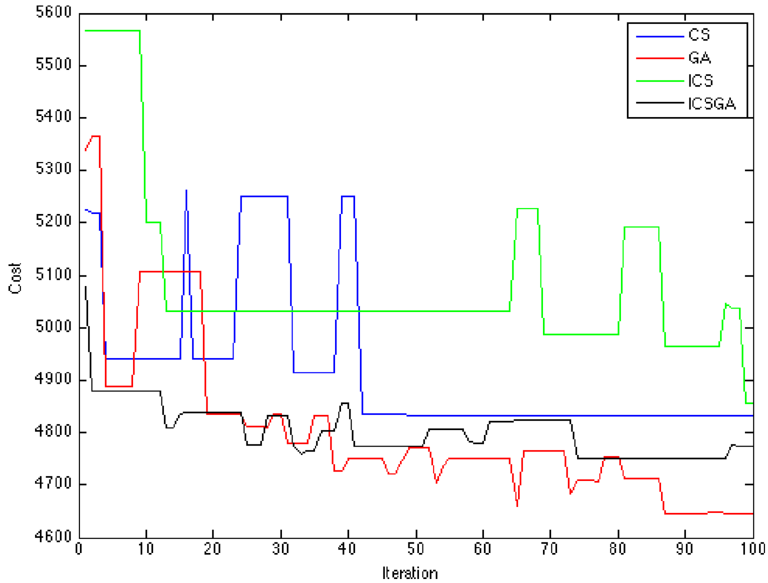

Figure 13. The convergence paths of TI based on algorithms.

Table 5. Comparison of optimum values and ranks of cost functions by ICSGA, ICS, GA and CS.

Algorithm	TU		TD		TI		TC		Total score	Total rank
	Value	Rank	Value	Rank	Value	Rank	Value	Rank		
ICSGA	5938	2	5387	2	4775	2	16 100	1	1.750	1
ICS	5889	1	5585	4	4857	4	16 331	2	2.750	3
GA	6321	4	5378	1	4645	1	16 344	3	2.250	2
CS	6195	3	5417	3	4831	3	16 443	4	3.250	4

6. Conclusion

This study links between the model of stochastic and deterministic inventory control problem which is fairly new. It is observed that proposed model has different view point from the original model. The proposed supply chain model deals with downstream, upstream and inventory costs. Downstream cost is along with total cost of sending finished-goods from focal company to the customer, and upstream cost is accompanied by all costs related to receive finished-goods from suppliers to the focal companies' inventories. In this model, SAPSR&S are used to deal with stochastic demands. So, these models can help the practitioners of the industrial management who face the uncertain demands that do not follow a probability distribution. Nature inspired meta-heuristic approaches are proved to be dominant techniques to attract combinatorial optimization problems in generating near optimal solutions. In this paper, ICSGA algorithm has been used to find near good quality solutions to document stochastic inventory control problem and proposed approach is compared with the existing popular techniques generated by CS, ICS and GA. It is observed that the performance of ICSGA algorithm is as good as GA in some cases and generally better in most situations. We also have showed that the proposed model is more suitable for the practical applications, especially in supply chain. Three hybrid methods through integrating ICS and GA have been validated using a numerical example. The experimental results indicate that hybrid method is better than using one algorithm alone. Consequently, we may suggest that ICSGA is superior to the others, among the three existing methods. The major limitation of this proposed model is that theoretical analyses of the proposed optimization techniques are not compared, only numerical comparisons have been drawn. In future, one can develop theory and practices of this proposed model to find out well tuned parameters in fuzzy environment. Mutiobjective version of this model can be studied further using NSGA-II and Neuro-fuzzy techniques. In this study, we perform a simulation-based optimization built on an simulated annealing algorithm in an inventory problem. Since there are many successful metaheuristic methods recently proposed, it would be interesting to apply these approaches instead of simulated annealing. In other hand, other random searches methods could be used to generate additional candidate solutions.

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