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A Stochastic Bi-Objective Mathematical Model for Optimizing a Production and Distribution System with Stochastic Demand and Stochastic Lead Time

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KEYWORDS

Supply chain management;
Bi Objective mathematical model;
Selective Firefly algorithm (SFA);
Probabilistic demand;
Probabilistic delivery lead time.

ABSTRACT

In the current study, a production and distribution network (PDN) is formulated to deliver the products to both inland and outland customers in the least amount of time and optimize the total profit of the network, simultaneously. The proposed network is a multi-stage PDN with multi suppliers, multi producers, multi entrepots, multi retailers, and multi inland and outland customers with multi-time period horizon with allowable shortage. A mixed integer-programming model is designed to minimize total cost of the system and minimize total delivery lead time. We applied a novel heuristic method called selective firefly algorithm (SFA) in order to solve several sized, especially real-world, instances. Finally, the performance of the proposed algorithm is examined by solving several sized instances. The results indicated that the proposed algorithm is of higher performance.

1. Introduction and Literature Review

The integrated production distribution network (PDN) as one of the most important optimization problems in supply chain management has attracted the attention of many researchers (1). The comprehensive form of a PDN includes supplier, producer, distributer, retailer, and customer that are scarcely considered in the literature.

Demand and delivery lead time can be two main parameters that are under uncertainty in the major of supply networks. Covering the uncertainty of these factors can be profitable to increase the customer satisfaction. The stochastic assumption of some parameters in both constraints and objective functions, considering probability distribution for uncertain parameters, is rarely applied. Chance constraint is a method for covering the uncertainty of the mathematical models. This approach transforms the stochastic model to a deterministic form, where some parameters of the model are uncertain and constraints are required to parallel to specified confidence level (2).

There are several factors, such as limited production capacity of the facilities and high fixed transportation cost, which cause delay in delivering the products to customers. In these conditions, part of the customers' demands may be considered as backorder; however, this assumption is not used in many of the former

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studies.
Therefore, in the problem under study, there are three main decisions to make: considering a comprehensive PDN from supplier to final customer, covering the customers' demands, and delivery lead time under probable conditions with allowable shortage.
Altiparmak et al. proposed a three-stage PDN and designed a mathematical model for the network. They introduced a new solution approach based on genetic algorithm (GA) to find near-optimum solutions (3). Boudia et al. presented a PDN and designed a mixed integer linear programming model (MILPM) with minimizing the total cost of the system for the proposed network. (4). Thanh et al. presented a PDN with multi-product and multi-planning horizon. They proposed a MILPM to minimize total cost of the system (5). Kazemi et al. introduced a PDN and proposed a MILP model to minimize the production, inventory, and transportation cost of the system (6). Calvete and Galé introduced a multi-objective planning for a PDN with multi producers, multi distribution centers, and multi retailers (7).
Peidro et al. studied a PDN with multi transportation types and multi time period horizons. The proposed network is formulated in the form of MILPM to minimize total cost of the system. Some parameters, such as demand and transport lead time, are assumed under uncertainty and apply fuzzy theory to cover these uncertainties (8). Cardona-Valdés et al. proposed a PDN and developed a stochastic optimization model under demand uncertainty (9). Wang et al. studied a one-stage PDN with stochastic demand. They designed a stochastic MILPM to maximize total profit of the system. They applied GA with efficient greedy heuristic to solve the problem (10). Amorim et al. presented a PDN with perishable products. They developed a simple hybrid genetic heuristic to solve the proposed model (11). Kadadevaramath et al. developed a two-stage PDN with single period horizon (12). Varthanan et al. studied an integrated PDN with stochastic demand. They considered a MILPM to minimize the total cost of the network (13).
Zamarripa et al. presented a PDN with multi time period. They designed a MILPM to minimize total cost of the system. The GA is used to solve the model (14). Bilgen and Çelebi introduced a MILP model for a PDN and solved the problem using simulation method (15). Kumar and Tiwari considered a PDN with multi time periods. They modeled the proposed system as mixed integer nonlinear problem (MINLP) by minimizing the network cost along with determining facility location and capacity (16). Latha Shankar et al. presented a PDN and designed a MINLP to minimize the total cost and maximize the fill rate (17). Liu and Papageorgiou presented a two-stage PDN with multi time period horizons. They proposed a MILPM framework to optimize the proposed network (18). Nasiri et al. proposed a multi-stage PDP with uncertain demand. They designed a mathematical programming model to minimize the total cost of the network. A heuristic method based on GA is proposed to solve the model (19). Bashiri and Rezaei proposed a relocation model in a supply chain network under uncertain environment. They applied a two-stage stochastic approach, the sample average approximation approach integrated with the Bender's decomposition approach to improve their model results (20).
Abraham et al. introduced a PDP with multi time periods. They used B&B method applying LINGO solver to solve the small instances, and a GA approach is applied to solve the larger instances (21). Ghodratnama et al. presented a robust mathematical model for a p-hub covering problem to minimize the total cost of the system. They applied a robust optimization theory to solve the model and compare the results to determined values by deterministic MILP model (22). Khalifehzadeh et al. presented a multi-stage PDN with multiple time periods. They designed a MILPM to minimize the total cost of the system and maximize the reliability of transportation system (1). Alizadeh Afrouzy et al. presented a multi-stage PDN and formulated a multi-objective MILPM to maximize the total profit of the system, the satisfaction level of customers, and production of the developed and new products (23). Sadeghian developed an inventory model with stochastic and irregular demands. The objective functions of the model include expected positive inventory level, expected negative inventory level, and inventory confidence level (24). Hosseini-Motlagh et al. introduced a MILP model for blood supply chain network design with multiple time periods. They used a robust programming approach to cover the uncertainty of the network. They applied two criteria including mean and standard deviation of constraint violations to examine the performance of the robust approach (25).
Birim studied a PDN with several transportation vehicles at different operational costs. The proposed system is formulated in the form of

MILPM to minimize total transportation costs and the fixed costs of the vehicles (26). Chan et al. studied a two-stage PDN with uncertain demand and multi truck types with different hiring cost. They designed a multi-objective mathematical model and used a heuristic algorithm along with the non-dominated sorting GA (NSGA-II) to produce much better solutions (27). Fathian et al. considered a two-stage PDN with uncertain customers' demands (28). Ma et al. proposed an integrated two-stage PDN with uncertain transportation costs. The objective of the proposed model minimizes the total global cost of the network. They developed a hybrid two-stage GA to solve the proposed model (29). Govindan and Fattahi proposed a PDN with uncertain customers' demands and designed a MILPM to minimize the total cost of the system (30). Hasani proposed a mathematical model for an electric power supply chain network under uncertainty with minimizing the total cost of the system. The proposed model is solved by Benders decomposition algorithm. The performance of solution algorithm is examined using data from the Tehran Regional Electric Company (31).

Jabbarzadeh et al. introduced a PDN and designed a MILPM for the proposed network to minimize the total cost of the system. The customers' demands are assumed under uncertainty (32). Fahimnia et al. introduced a multi-stage PDN and proposed a multi-objective MINLP to minimize total cost of the system and minimize the total carbon emissions. They applied three metaheuristic algorithms, GA, Simulated Anealing (SA), and Cross Entropy (CE), to solve the model (33).

In the current study, a comprehensive PDN is considered including multi suppliers, producers, potential entrepots, retailers, and inland and outland customers with multiple time periods and allowed shortage. The customers are classified based on their shortage costs as the highest priority is given to customers with the highest unit shortage cost. We formulate the proposed PDN as a mathematical programming model. The proposed model is validated by applying several instances in different sizes. Small-sized instances are solved by LINGO solver. Furthermore, we proposed a novel algorithm based on FA called SFA for solving large-sized instances.

The paper is organized as follows. In Section 2, the problem under study is described. In Section 3, the mathematical model of the problem and uncertainty concepts of the proposed network are presented. In Section 4, heuristic method based on FA is applied. In Section 5, the results of several numerical instances are examined. In Section 6, the paper is concluded.

2. Problem Description

The considered PDN includes suppliers, producers, entrepots, retailers, and customer zones. The required raw materials are transferred from the suppliers to producers. The main purposes of the proposed PD system are tactical decisions to activate or inactivate an entrepot in each period and operational decisions to distribute the commodities through the network. Each entrepot includes an entrance for receiving the products and a dock for arranging the products, transmitting them to vehicles, and transferring them to customers. It is assumed that there is not any fixed storage in the entrepots and products have only a short delay. The customers are divided into two generic classes consisting of internal and external that are related to inland and outland customers, respectively.

Delivery of the products to consumers in the shortest time is an efficacious factor in increasing the satisfaction level of consumers. Nevertheless, in some real world networks, having shorter delivery time needs better transportation systems with higher cost. In the proposed network, we assume several transportation systems with different delivery time with an inverse relation between delivery time and transportation cost. The schematic presentation of the proposed network is demonstrated in Fig 1. Each supplier is able to produce different kinds of raw materials, and each facility can produce all types of products. Unmet customers' demands are backordered; however, the whole demands must be met by the last time period. Several transportation systems with different lead times are assumed in all parts of the network. Each transportation system has restricted capacity; however, it can move several times at each time period in a given route.

To achieve a reasonable cost of the system and an adequate delivery lead time in whole network, we consider two objectives including minimizing the total cost of the system and minimizing the total delivery lead time.

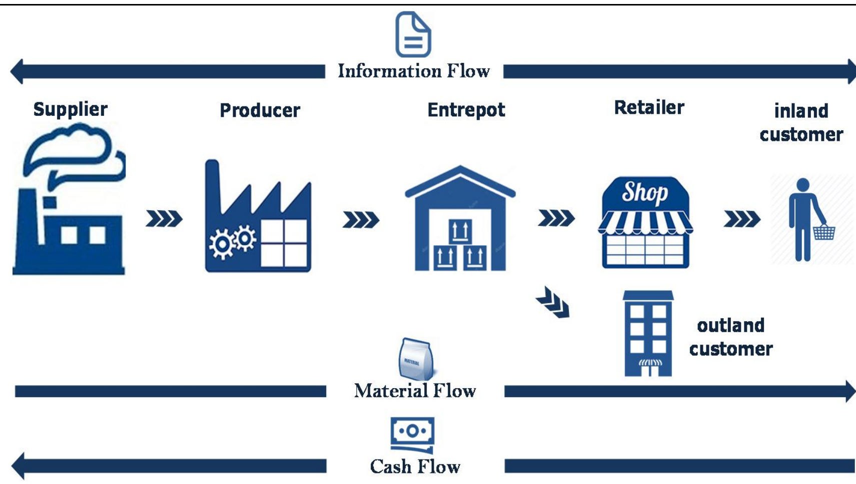


Fig. 1. Structure of the concerned multi stage logistics network

The proposed supply chain problem can be defined as follows:

Given the input data:

- Number of suppliers, plants, entrepots, retails, inland and outland customers;
- Variety of raw material and products;
- Required raw material for producing each product;
- producing, transporting, and holding cost of products,
- Backorder cost of each product,
- Time period horizon,
- Regular time and overtime in each period,
- Required setup and process time for producing the products,
- Delivery lead time,
- Volume of each raw material and product,
- Storage capacity of each plant and retail store,
- Customers' demands,

The key variables to be determined:

- Active entrepots and retail stores in each period,
- Quantity of transferred raw material from each supplier to producers in each period,
- Quantity of manufactured product by each producer in each period,
- Quantity of transferred product from each active entrepot to active retail store and outland customers by each transportation system,
- Quantity of transferred product from each active retail store to inland customers by each transportation system,
- Quantity of backorder demand of each inland and outland customer in each period.

3. Mathematical Formulation

The main objective of the proposed network is to minimize the total cost. However, one of the most important factors in improving the customer satisfaction rate is delivery of the products in the least amount of time. In the current study, we consider multi transportation systems with fixed and variable transportation costs dependent on elapsed time to deliver the products from producers to final customers. Therefore, there are two conflicting objectives including minimizing the total cost of the system and minimizing the delivery lead time. The features of the proposed model are described in detail as follows:

3-1. Assumptions

The assumptions of the proposed model are as follows:

- Each plant can receive raw material from several suppliers.
- Each plant is able to produce all ranges of products.
- All plants can produce products of the same quality.
- Each entrepot receives products from several plants.
- Products are transported by limited capacity vehicles.
- There are several transportation systems to deliver the products to customers.
- Retail stores are allowed to keep inventories at the end of each period.
- Customer demand can be fulfilled by several retail stores.
- Selling price for a specific product can be dissimilar in different customer zones.
- Backorder is allowed and unfulfilled

demands in a period can be carried over to the next period.

3-2. Notations

The following notations have been used to solve the proposed model:

Sets, Indices:

I	suppliers indexed by $i \in \{1, \dots, I\}$
J	plants indexed by $j \in \{1, \dots, J\}$
K	potential entrepots indexed by $k \in \{1, \dots, K\}$
D	potential retail stores indexed by $d \in \{1, \dots, D\}$
C	inland customer zones indexed by $c \in \{1, \dots, C\}$
C'	outland customer zones indexed by $c' \in \{1, \dots, C'\}$
Q	transportation systems indexed by $q \in \{1, \dots, Q\}$
R	raw materials indexed by $r \in \{1, \dots, R\}$
P	products indexed by $p \in \{1, \dots, P\}$
T	time periods indexed by $t \in \{1, \dots, T\}$

Parameters:

$rtime_{jt}$	available regular time of plant j in period t
$otime_{jt}$	available overtime of plant j in period t
pt_{jp}	processing time for producing product p in plant j
st_{jp}	set-up time for producing product p in plant j
sc_{jpt}	set-up cost for producing product p in plant j in period t
rp_{irt}	unit price of raw material r at supplier i in period t
rmc_{pt}	unit production cost of product p at a regular time of period t
omc_{pt}	unit production cost of product p in overtime of period t
ltp_{jk}^{q}	the time of shipping each product from plant j to entrepot k by transportation type q
$ltp_{kd}^{\prime q}$	the time of shipping each product from entrepot k to retail store d by transportation type q
$ltp_{dc}^{\prime\prime q}$	the time of shipping each product from retail store d to inland customer c by transportation type q
$ltp_{kc'}^{\prime\prime\prime q}$	the time of shipping each product from entrepot k to outland customer c' by transportation type q
at	average time for delivering the products to inland customer
at'	average time for delivering the products to outland customer
$rftc_{ijt}$	fixed transportation cost from supplier i to plant j in period t
$rutc_{ijrt}$	unit transportation cost of raw material r from supplier i to plant j in period t
$pftc_{jkt}^{q}$	fixed transportation cost from plant j to entrepot k by transportation type q in period t
$putc_{jkpt}^{q}$	unit transportation cost of product p from plant j to entrepot k by transportation type q in period t
$pftc_{kdt}^{\prime q}$	fixed transportation cost from entrepot k to retail store d by transportation type q in period t
$putc_{kdpt}^{\prime q}$	unit transportation cost of product p from entrepot k to retail store d by transportation type q in period t
$pftc_{dct}^{\prime\prime q}$	fixed transportation cost from retail store d to inland customer zone c by transportation type q in period t
$putc_{dcpt}^{\prime\prime q}$	unit transportation cost of product p from retail store d to inland customer zone c by transportation type q at in period t
$pftc_{kc't}^{\prime\prime\prime q}$	fixed transportation cost from entrepot k to outland customer zone c' by transportation type q in period t
$putc_{kc'pt}^{\prime\prime\prime q}$	unit transportation cost of product p from entrepot k to outland customer zone c' by transportation type q in period t
vr_r	volume of Raw material r
vp_p	volume of product p

dem_{cpt}	demand of inland customer c for product p in period t
$dem'_{c'pt}$	demand of outland customer c' for product p in period t
hcr_{jrt}	holding cost of each raw material r in plant j in period t
hcp_{jpt}	holding cost of each product p in plant j in period t
hcp'_{dpt}	holding cost of each product p in retail store d in period t
nu_{rp}	required raw material r for producing a product p
$capv$	capacity of each vehicle
$capf_j$	storage capacity of plant j
$capr_d$	storage capacity of retail store d
acc_{kt}	activation cost of entrepot k in period t
boc_{cpt}	backordering cost of each product p for inland customer zone c in period t
$boc'_{c'pt}$	backordering cost of each product p for outland customer zone c' in period t
M	a positive large number

Decision variables:

X_{jpt}	product p produced by plant j in regular time of period t
X'_{jpt}	product p produced by plant j in overtime of period t
RS_{ijrt}	raw material r Procured from supplier i to plant j in period t
PS^{q}_{jkpt}	product p shipped from plant j to entrepot k by transportation type q in period t
PS'^{q}_{kdpt}	product p shipped from entrepot k to retailer d by transportation type q in period t
PS''^{q}_{dcpt}	product p shipped from retailer d to inland customer zone c by transportation type q in period t
$PS'''^{q}_{kc'pt}$	product p shipped from entrepot k to outland customer zone c' by transportation type q in period t
W_{jpt}	1 if product p is manufactured by plant j in period t, 0 otherwise
Y_{kt}	1 if entrepot k is activated in period t, 0 otherwise
RSU_{jrt}	remaining amount of raw material r in plant j at the end of period t
PSU_{jpt}	remaining amount of product p in plant j at the end of period t
PSU'_{dpt}	remaining amount of product p in retailer zone d at the end of period t
BC_{cpt}	backorder level of product p for inland customer c in period t
$BC'_{c'pt}$	backorder level of product p for outland customer c' in period t
RNV_{ijt}	Quantity of moving a vehicle from supplier i to plant j in period t
PNV^{q}_{jkt}	Quantity of moving a vehicle of transportation type q from plant j to entrepot k in period t
PNV'^{q}_{kdt}	Quantity of moving a vehicle of transportation type q from entrepot k to retail store d in period t
PNV''^{q}_{dct}	Quantity of moving a vehicle of transportation type q from retail store d to inland customer zone c in period t
$PNV'''^{q}_{kc't}$	Quantity of moving a vehicle of transportation type q from entrepot k to outland customer zone c' in period t

3-3. Formulation of the model

The optimal or near-optimal sales quantity, production rate, and total delivery lead time are obtained using the following mathematical model, which minimizes the total cost (Min_{cost}) and minimizes the total delivery lead time (Min_{dltime}) of the proposed network, simultaneously.

$$
\begin{aligned}
Min_{cost} = & \sum_{\forall i}\sum_{\forall j}\sum_{\forall r}\sum_{\forall t}\sum_{\forall q}(RS_{ijrt}.rp_{irt}) + \sum_{\forall j}\sum_{\forall p}\sum_{\forall t}(W_{jpt}.sc_{jpt}) + \sum_{\forall j}\sum_{\forall p}\sum_{\forall t}(X_{jpt}.rmc_{pt} \\
& + X'_{jpt}.omc_{pt}) + \sum_{\forall j}\sum_{\forall r}\sum_{\forall t}(RSU_{jrt}.hcr_{jrt}) + \sum_{\forall j}\sum_{\forall p}\sum_{\forall t}(PSU_{jpt}.hcp_{jpt}) \\
& + \sum_{\forall d}\sum_{\forall p}\sum_{\forall t}(PSU'_{dpt}.hcp'_{dpt}) + \sum_{\forall i}\sum_{\forall j}\sum_{\forall t}\sum_{\forall q}(RNV_{ijt}.rftc_{ijt}) \\
& + \sum_{\forall i}\sum_{\forall j}\sum_{\forall r}\sum_{\forall t}\sum_{\forall q}(RS_{ijrt}.rutc_{ijrt}) \\
& + \sum_{\forall j}\sum_{\forall k}\sum_{\forall t}\sum_{\forall q}\left(PNV^{q}_{jkt}.pftc^{q}_{jkt}\right) + \sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.putc^{q}_{jkpt}) \\
& + \sum_{\forall k}\sum_{\forall d}\sum_{\forall t}\sum_{\forall q}\left(PNV'^{q}_{kdt}.pftc'^{q}_{kdt}\right) + \sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.putc'^{q}_{kdpt}) \\
& + \sum_{\forall d}\sum_{\forall c}\sum_{\forall t}\sum_{\forall q}\left(PNV''^{q}_{dct}.pftc''^{q}_{dct}\right) + \sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.putc''^{q}_{dcpt}) \\
& + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall t}\sum_{\forall q}\left(PNV'''^{q}_{kc't}.pftc'''^{q}_{kc't}\right) + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.putc'''^{q}_{kc'pt}) \\
& + \sum_{\forall k}\sum_{\forall t}(Y_{kt}.acc_{kt}) + \sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\left(BC_{cpt}.boc_{cpt}\right) + \sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\left(BC'_{c'pt}.boc'_{c'pt}\right)
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
Min_{dltime} = & \sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.ltp^{q}_{jk}) + \sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.ltp'^{q}_{kd}) \\
& + \sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.ltp''^{q}_{dc}) + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.ltp'''^{q}_{kc'}) \\
& + \sum_{\forall c}\sum_{\forall p}\sum_{\forall t}(BC_{cpt}.at) + \sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}(BC'_{c'pt}.at')
\end{aligned} \tag{2}
$$

S.t:

$$\sum_{\forall p}\left(W_{jpt}.st_{jp}\right) + \sum_{\forall p}(X_{jpt}.pt_{jp}) \le rtime_{jt}, \quad \forall j,t \tag{3}$$

$$\sum_{\forall p}(X'_{jpt}.pt_{jp}) \le otime_{jt}, \quad \forall j,t \tag{4}$$

$$X_{jpt} \ge X'_{jpt}, \quad \forall j,p,t \tag{5}$$

$$X_{jpt} + X'_{jpt} \le W_{jpt}.M, \quad \forall j,p,t \tag{6}$$

$$\sum_{\forall i}\sum_{\forall q}\left(RS_{ijr1}\right) = \sum_{\forall p}\left(X_{jp1}.nu_{rp}\right) + RSU_{jr1}, \quad \forall j,r \tag{7}$$

$$\sum_{\forall i}\sum_{\forall q}\left(RS_{ijrt}\right) + RSU_{jr(t-1)} = \sum_{\forall p}\left(X_{jpt}.nu_{rp}\right) + RSU_{jrt}, \quad \forall j,r,t>1 \tag{8}$$

$$X_{jp1} + X'_{jp1} = \sum_{\forall k}\sum_{\forall q} PS^{q}_{jkp1} + PSU_{jp1}, \quad \forall j,p \tag{9}$$

$$X_{jpt} + X'_{jpt} + PSU_{jp(t-1)} = \sum_{\forall k}\sum_{\forall q} PS^{q}_{jkpt} + PSU_{jpt}, \quad \forall j,p,t>1 \tag{10}$$

$$\sum_{\forall j}\sum_{\forall q} PS^{q}_{jkpt} = \sum_{\forall d}\sum_{\forall q} PS'^{q}_{kdpt} + \sum_{\forall c'}\sum_{\forall q} PS'''^{q}_{kc'pt}, \quad \forall k,p,t \tag{11}$$

$$\sum_{\forall k}\sum_{\forall q} PS'^{q}_{kdp1} = \sum_{\forall c}\sum_{\forall q} PS''^{q}_{dcp1} + PSU'_{dp1}, \quad \forall d,p \tag{12}$$

$$\sum_{\forall k}\sum_{\forall q} PS'^{q}_{kdpt} + PSU'_{dp(t-1)} = \sum_{\forall c}\sum_{\forall q} PS''^{q}_{dcpt} + PSU'_{dpt}, \quad \forall d,p,t>1 \tag{13}$$

$$\sum_{\forall d}\sum_{\forall q} PS''^{q}_{dcp1} + BC_{cp1} = dem_{cp1}, \ \ \forall c,p \tag{14}$$

$$\sum_{\forall d}\sum_{\forall q} PS''^{q}_{dcpt} + BC_{cpt} = dem_{cpt} + BC_{cp(t-1)}, \ \ \forall c,p,t>1 \tag{15}$$

$$\sum_{\forall d}\sum_{\forall q} PS''^{q}_{dcpT} = dem_{cpT} + BC_{cp(T-1)}, \ \ \forall c,p \tag{16}$$

$$\sum_{\forall k}\sum_{\forall q} PS'''^{q}_{kc'p1} + BC'_{c'p1} = dem'_{c'p1}, \ \ \forall c',p \tag{17}$$

$$\sum_{\forall k}\sum_{\forall q} PS'''^{q}_{kc'pt} + BC'_{c'pt} = dem'_{c'pt} + BC'_{c'p(t-1)}, \ \ \forall c',p,t>1 \tag{18}$$

$$\sum_{\forall k}\sum_{\forall q} PS'''^{q}_{kc'pT} = dem'_{c'pT} + BC'_{c'p(T-1)}, \ \ \forall c',p \tag{19}$$

$$\sum_{\forall r}(RS_{ijrt}.vr_r) \le RNV_{ijt}.capv, \ \ \forall i,j,t \tag{20}$$

$$\sum_{\forall p}(PS^{q}_{jkpt}.vp_p) \le PNV^{q}_{jkt}.capv, \ \ \forall j,k,t,q \tag{21}$$

$$\sum_{\forall p}(PS'^{q}_{kdpt}.vp_p) \le PNV'^{q}_{kdt}.capv, \ \ \forall k,d,t,q \tag{22}$$

$$\sum_{\forall p}(PS''^{q}_{dcpt}.vp_p) \le PNV''^{q}_{dct}.capv, \ \ \forall d,c,t,q \tag{23}$$

$$\sum_{\forall p}(PS'''^{q}_{kc'pt}.vp_p) \le PNV'''^{q}_{kc't}.capv, \ \ \forall k,c',t,q \tag{24}$$

$$\sum_{\forall r}(RSU_{jrt}.vr) + \sum_{\forall p}(PSU_{jpt}.vp) \le capf_j, \ \ \forall j,t \tag{25}$$

$$\sum_{\forall p}(PSU'_{dpt}.vp) \le capr_d, \ \ \forall d,t \tag{26}$$

$$\sum_{\forall j}\sum_{\forall p}\sum_{\forall q} PS^{q}_{jkpt} \le Y_{kt}.M, \ \ \forall k,t \tag{27}$$

$$\begin{aligned}
&X_{jpt}, X'_{jpt} \ge 0, Integer, \ \ \forall j,p,t\\
&RS_{ijrt}, PS^{q}_{jkpt}, PS'^{q}_{kdpt}, PS''^{q}_{dcpt}, PS'''^{q}_{kc'pt} \ge 0, Integer, \ \ \forall i,j,k,d,c,c',r,p,t,q\\
&RSU_{jrt}, PSU_{jpt}, PSU'_{dpt} \ge 0, Integer, \ \ \forall j,d,r,p,t\\
&RNV_{ijt}, PNV^{q}_{jkt}, PNV'^{q}_{kdt}, PNV''^{q}_{dct}, PNV'''^{q}_{kc't} \ge 0, Integer, \ \ \forall i,j,k,d,c,c',t,q\\
&BC_{cpt}, BC'_{c'pt} \ge 0, Integer, \ \ \forall c,c',p,t
\end{aligned} \tag{28}$$

$$W_{jpt}, Y_{kt} \in \{0,1\}, \ \ \forall j,k,p,t \tag{29}$$

The objective function (1) is to minimize the total cost of the system including purchasing cost of raw material, setup cost of the production lines, manufacturing cost of the products at a regular time and overtime of each period, holding cost of the raw material and products in production facilities, holding cost of the products in retailers, fixed and variable costs of transferring raw material from suppliers to production facilities, fixed and variable costs of transferring the products to inland and outland customers, activation cost of entrepots and retailers, and backordered cost of inland and outland customers. The objective function (2) is to minimize the total delivery lead time from suppliers to final customers with regard to transportation type and amount of backordering demand of inland and outland customers. The first five parts of this equation are related to required time for delivering raw materials and products from suppliers to final customers, and the last two parts are related to delay elapsed for delivering backordered.

Constraints (3) and (4) ensure that elapsed setup and production time in each production facility do not exceed the available regular time and overtime in each period. Constraint (5) controls that overtime in production facilities is not activated before regular time. Constraint (6) controls that each production facility can manufacture each product if the corresponding binary variable takes value of one. Constraints (7) and (8) specify the balanced inventory of the raw material in production centers. Constraints (9) and (10) specify the balanced inventory of the products in production centers. Constraint (11) specifies the balanced inventory of the products in activated entrepots. Constraints (12) and (13) specify the balanced inventory of the products in activated retailers. Constraints (14) and (15) represent the backorder balance equation in each inland customer's site. Constraint (16) is concerned with the backorder balance equation of inland customers' demand in the last period. Constraints (17) and (18) represent the backorder balance equation in each outland customer's site. Constraint (19) is concerned with the backorder balance equation of outland customers' demand in the last period. Constraint (20) specifies the amount of required vehicles to transport raw material from material suppliers to production facilities with considering capacity of the vehicles.

Constraints (21-24) specify amount of required vehicles to transport manufactured products in the network with considering capacity of the vehicles. Constraints (25) and (26) control the storage capacity of production facilities and retailer sites, respectively. Constraint (27) controls the activation of each potential entrepot. Constraints (28) and (29) define non-negativity, integer and binary status of decision variables, respectively.

3-4. Stochastic parameters of the model

In practice, some parameters of PDNs are uncertain. Customer demand and delivery lead time are typically uncertainly quantified in supply chain procedures (34). In such situations, traditional models with constant parameters cannot be suitable to cover the uncertainty of PDSs. In the current study, some parameters of the proposed network including amount of inland and outland customers' demands and delivery lead time are assumed uncertain. These two parameters are stochastic or probabilistic in nature (2). Therefore, the proposed model is changed to stochastic form in the following sections.

3-4-1. Delivery lead time

The real delivery lead time may differ from the planned delivery lead time due to transportation mode and many other factors which cause delay in delivery time. Hence, delivery lead time is probabilistic in real cases. In the current study, delivery lead time is assumed to be probabilistic with known mean and standard deviation. The mean and standard deviation data are based on historical evidences. The following steps are applied to convert the stochastic delivery lead time to deterministic form:

Step1: Assume that L is the aspired time related to the second objective function (min_{dltime}). This aspiration level can be obtained by realizing the optimal solution of solving delivery lead time objective, separately (Eq. 30).

$$L=\sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.ltp^{q}_{jk})+\sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.ltp'^{q}_{kd})$$
$$+\sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.ltp''^{q}_{dc})+\sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.ltp'''^{q}_{kc'})$$
$$+\sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC_{cpt}.at_{t})+\sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC'_{c'pt}.at'_{t}) \tag{30}$$

Step2: The mean value of delivery lead time is replaced into the second objective function. Therefore, Eq.2 is changed as follows (Eq. 31).

(31)

$$Min_{dltime} = \sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.\mu_{ltp}{}^{q}_{jk}) + \sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.\mu_{ltp}{}'^{q}_{kd}) + \sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.\mu_{ltp}{}''^{q}_{dc}) + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.\mu_{ltp}{}'''^{q}_{kc'}) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC_{cpt}.at_t) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC'_{c'pt}.at'_t)$$

Step3: With using chance constraint procedure, the probabilistic equation for delivery lead time objective function is written as in inequality Eq. 32.

$$P\left[L > \sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.\mu_{ltp}{}^{q}_{jk}) + \sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.\mu_{ltp}{}'^{q}_{kd}) + \sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.\mu_{ltp}{}''^{q}_{dc}) + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.\mu_{ltp}{}'''^{q}_{kc'}) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC_{cpt}.at_t) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC'_{c'pt}.at'_t)\right] \le \alpha_{lt} \Rightarrow \tag{32}$$

where α_{lt} is risk level for the obtained value of lead time to be greater than the aspired level.
Using chance constraint procedure presented by (35), the probabilistic inequality (32) is converted to deterministic form as follows (Eqs. 33-35):

$$P\left[L \le \sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.\mu_{ltp}{}^{q}_{jk}) + \sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.\mu_{ltp}{}'^{q}_{kd}) + \sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.\mu_{ltp}{}''^{q}_{dc}) + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.\mu_{ltp}{}'''^{q}_{kc'}) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC_{cpt}.at_t) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC'_{c'pt}.at'_t)\right] \ge (1-\alpha_{lt}) \Rightarrow \tag{33}$$

$$F_L\left[\sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.\mu_{ltp}{}^{q}_{jk}) + \sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.\mu_{ltp}{}'^{q}_{kd}) + \sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.\mu_{ltp}{}''^{q}_{dc}) + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.\mu_{ltp}{}'''^{q}_{kc'}) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC_{cpt}.at_t) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC'_{c'pt}.at'_t)\right] \ge (1-\alpha_{lt}) \Rightarrow \tag{34}$$

$$\sum_{\forall j}\sum_{\forall k}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS^{q}_{jkpt}.\mu_{ltp}{}^{q}_{jk}) + \sum_{\forall k}\sum_{\forall d}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'^{q}_{kdpt}.\mu_{ltp}{}'^{q}_{kd}) + \sum_{\forall d}\sum_{\forall c}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS''^{q}_{dcpt}.\mu_{ltp}{}''^{q}_{dc}) + \sum_{\forall k}\sum_{\forall c'}\sum_{\forall p}\sum_{\forall t}\sum_{\forall q}(PS'''^{q}_{kc'pt}.\mu_{ltp}{}'''^{q}_{kc'}) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC_{cpt}.at_t) + \sum_{\forall p}\sum_{\forall c}\sum_{\forall t}(BC'_{c'pt}.at'_t) \ge F_L^{-1}(1-\alpha_{lt}) = Min^{*}_{dltime} \tag{35}$$

where F_L *and* F_L^{-1} are cumulative distribution function and inverse cumulative distribution function for random delivery lead time at given risk level α_{lt} , respectively. $F_L^{-1}(1-\alpha_{lt})$ is replaced by optimal aggregated delivery lead time obtained when entire resources and constraints are fully consumed considering the objective Min_{dltime} individually (Min^{*}_{dltime}) (2). Therefore, Eq. 35 is added to the proposed model as a constraint.

3-4-2. Customers' demands

Demand uncertainty is an indisputable fact in the major real cases. Prediction of demand to obtain an acceptable production and distribution planning is an important issue in all PDNs. Nevertheless, the demand in several studies is considered as a deterministic parameter. In some other studies, the demand is assumed under uncertainty with a specified distribution function, and it is simplified and converted to deterministic form with considering the mean values. Stochastic models can be more appropriate to tackle these uncertainties in orders (36). Since error in forecasting demands is often considered to be normally distributed, the demands will be assumed to be normal (37). Thus, in the current study, the demand pattern is supposed as stochastic with a specified normal distribution. With considering both inland and outland customers' demand in the current network, some related constraints in the proposed model are transferred to stochastic form. A relevant technique to convert the stochastic constraints into equivalent deterministic constraints is chance constraint technique ((38), (2)). Consequently, we apply multi-chance constraint to cover these uncertainties.

It is assumed that parameters of the demand of inland customers (dem_{cpt}) and outland customers ($dem'_{c'pt}$) follow independent normal distribution $N\sim(\mu_{dem_{cpt}}, \sigma_{dem_{cpt}})$ and $N\sim(\mu'_{dem'_{c'pt}}, \sigma'_{dem'_{c'pt}})$, respectively. The mean and standard deviation data are calculated based on historical evidences. The additional notations used are as follows:

$\mu_{dem_{cpt}}$	Expected value of inland customer's demand c for product p in period t
$\sigma_{dem_{cpt}}$	Standard deviation of inland customer's demand c for product p in period t
$f_{cpt}(dem_{cpt})$	Probability distribution function of inland customer's demand c for product p in period t
$F_{cpt}(dem_{cpt})$	Cumulative distribution function of inland customer's demand c for product p in period t
$\mu'_{dem'_{c'pt}}$	Expected value of outland customer's demand c' for product p in period t
$\sigma'_{dem'_{c'pt}}$	Standard deviation of outland customer's demand c' for product p in period t
$f_{c'pt}(dem'_{c'pt})$	Probability distribution function of outland customer's demand c' for product p in period t
$F_{c'pt}(dem'_{c'pt})$	Cumulative distribution function of outland customer's demand c' for product p in period t

Constraints (14-16) and (17-19) are related to inland and outland customers' demand in all time period, respectively. By using chance constraint technique, the probabilistic equation for Eq.16 can be written as probabilistic inequality (36).

$$p\left(\sum_{\forall d} PS''_{dcp1} + BC_{cp1} < dem_{cp1}\right) < \alpha_c, \ \forall c,p \tag{36}$$

Inequality (36) means that the possibility of nonfulfillment of constraint 14 is less than α_c, where $\alpha_c \in (0,1)$; consequently, confidence level of Constraint 14 is $1-\alpha_c$.

To convert Eq. 36 to a linear deterministic equivalent constraint, the following steps are written (Eqs. 37-39):

$$p\left(\sum_{\forall d} PS''_{dcp1} + BC_{cp1} < dem_{cp1}\right) < \alpha_c, \ \forall c,p \tag{37}$$

$$p\left(dem_{cp1} < \sum_{\forall d} PS''_{dcp1} + BC_{cp1}\right) \geq 1-\alpha_c, \ \forall c,p \tag{38}$$

$$\int_0^{\sum_{\forall d} PS''_{dcp1} + BC_{cp1}} f_{cpt}(dem_{cpt})\, d_{dem_{cpt}} \geq 1-\alpha_c, \ \forall c,p \tag{39}$$

If $f_i(x)$ is probability distribution function x, then $\int_0^c f_i(x)\, d_x$ is $F_i(c)$, called cumulative distribution function x. Consequently, Eq. 39 is converted to Eq. 40.

$$F_{cpt}(\sum_{\forall d} PS''_{dcp1} + BC_{cp1}) \geq 1 - \alpha_c, \ \forall c, p \tag{40}$$

Herein, $dem_{cpt} \sim N(\mu_{dem_{cpt}}, \sigma_{dem_{cpt}})$; therefore, Eq.44 can be rewritten as Eq.41:

$$\Phi\left[\frac{\left(\sum_{\forall d} PS''_{dcp1} + BC_{cp1}\right) - \mu_{dem_{cpt}}}{\sigma_{dem_{cpt}}}\right] \geq 1 - \alpha_c, \ \forall c, p \tag{41}$$

$$\Phi(Z) \geq 1 - \alpha_c, \ \forall c, p$$

Φ is standard normal distribution and a strictly increasing function on Z; hence, Eq.41 is converted to Eq. 42.

$$\frac{\left(\sum_{\forall d} PS''_{dcp1} + BC_{cp1}\right) - \mu_{dem_{cpt}}}{\sigma_{dem_{cpt}}} \geq Z_{1-\alpha_c}, \ \forall c, p \tag{42}$$

$$\left(\sum_{\forall d} PS''_{dcp1} + BC_{cp1}\right) \geq \sigma_{dem_{cp1}} . Z_{1-\alpha_c} + \mu_{dem_{cp1}}, \ \forall c, p \tag{43}$$

The same steps are followed for other related constraints. Consequently, Eqs. 14-19 are replaced by Eqs. 43-48, respectively.

$$\left(\sum_{\forall d} PS''_{dcpt} + BC_{cpt} - BC_{cp(t-1)}\right) \geq \sigma_{dem_{cpt}} . Z_{1-\alpha_c} + \mu_{dem_{cpt}}, \ \forall c, p, t > 1 \tag{44}$$

$$\left(\sum_{\forall d} PS''_{dcpT} - BC_{cp(T-1)}\right) \geq \sigma_{dem_{cpt}} . Z_{1-\alpha_c} + \mu_{dem_{cpt}}, \ \forall c, p \tag{45}$$

$$\left(\sum_{\forall k} PS'''_{kc'p1} + BC'_{c'p1}\right) \geq \sigma'_{dem'_{c'p1}} . Z_{1-\alpha_c} + \mu'_{dem'_{c'p1}}, \ \forall c', p \tag{46}$$

$$\left(\sum_{\forall k} PS'''_{kc'pt} + BC'_{c'pt} - BC'_{c'p(t-1)}\right) \geq \sigma'_{dem'_{c'pt}} . Z_{1-\alpha_c} + \mu'_{dem'_{c'pt}}, \ \forall c', p, t > 1 \tag{47}$$

$$\left(\sum_{\forall k} PS'''_{kc'pT} - BC'_{c'p(T-1)}\right) \geq \sigma'_{dem'_{c'pT}} . Z_{1-\alpha_c} + \mu'_{dem'_{c'pT}}, \ \forall c', p \tag{48}$$

The intent is to provide a 95% confidence level for demand forecasting in all time periods. Thus, with considering $\alpha_c = 0.05$ in the above inequalities, the fulfillment of Eqs. 14-19 with a 95% confidence level is ensured.

4. Solution Approaches

The introduced integrated model for the proposed supply chain network in the former section is a mixed integer programming model with several constraints. Solving these models in a reasonable time, especially in real world instances is main challenge in major part of researches. Generally, these models are hard to solve with applying traditional exact methods (39). In this section, we propose a novel meta-heuristic algorithm based on FA to achieve a near optimum solution for the proposed model.

4-1. Proposed Selective Firefly Algorithm

Firefly Algorithm (FA) is one of the swarm intelligence based algorithms that introduced by (40). FA is inspired from fireflies' behavior in nature. A vital factor in fireflies' life is *brightness* with several applications, such as warning predators and or showing its attractiveness for other fireflies. Amount of potency versus the predators and attractiveness value for others depend on the light intensity, distance between insects and the light absorption by environment (41). To simplify the traits of fireflies in applying the FA, three rules are considered, as follows ((42), (43), (44)):

- Fireflies are considered unisex, thus the attractiveness of fireflies is regardless of the sex.
- In the movement, less bright firefly move towards the brighter one.
- Brightness of each firefly indicates the quality of solution.

In standard FA, there are four important issues, consisting Light intensity, Attractiveness, Distance and Movement that are described as follows (41), (45).

At first, initial solutions are calculated. If consider a population with N members in a D dimensions environment, each solution is represented as follows (Eq. 49).

$$x_i = (x_{i1}, \dots, x_{iD}), \quad \text{for } i = 1, \dots, N \tag{49}$$

where x_i is i th solution in D dimensions environment.

Light Intensity represents the brightness of a firefly that is proportional to the objective function value and calculates using Eq. 50.

$$I(r) = I_0 . e^{-\gamma r^2} \quad (50)$$

where $I(r)$ is light intensity of a firefly in distance r , I_0 is original light intensity, r indicates the distance between two fireflies and γ is light absorption coefficient.

Attractiveness of a firefly is a decreasing function with a reverse relation to the distance that is calculated as follows (Eq. 51).

$$\beta(r) = \beta_0 . e^{-\gamma r^2} \quad (51)$$

where $\beta(r)$ is attractiveness of a firefly in distance r and β_0 is attractiveness at distance $r = 0$.

The distance between two fireflies i and j with x_i and x_j values is calculated according to Cartesian distance (Eq. 52).

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{D} (x_{ik} - x_{jk})^2} \quad (52)$$

where r_{ij} is the distance between two fireflies, i and j, with x_i and x_j values in a D-dimension environment. In the standard FA, the less bright firefly moves toward the brighter one. Assume that firefly i is less bright than firefly j; then, a new position of firefly i after moving toward firefly j is determined using Eq. 53.

$$x_i' = x_i + \beta_0 e^{-\gamma r^2} (x_i - x_j) + \alpha \varepsilon_i \quad (53)$$

where x_i' is the new position of firefly i, α is the step size scaling factor, and ε_i is the random factor generated by a uniform distribution with a range from 0 to 1.

In the optimization problems, each firefly is representative of a solution, and the light intensity of the firefly is equal to quality of the solution (46). In the first step, we have an initial population of fireflies that can be a random population. After that, two fireflies (two solutions) are compared and firefly with less brightness (weaker solution) moves toward brighter one (better solution). Then, all positions of fireflies are updated, and these steps continue until finishing the comparison of all fireflies. After generating the new population, these steps are repeated on the new population. The process is continued until satisfying the stop criterion.

The proposed SFA in the current research is explained as follows. To apply the proposed SFA, initially, some random solutions are generated as the first population. Each solution with a definite fitness function value is assumed as a firefly with specified brightness. The firefly with the highest brightness is selected as the best solution in the current population. Then, the selected firefly moves randomly, and the brightness of new location is calculated. If improvement is achieved, firefly in the new location is transmitted to the next population. Otherwise, the best solution in the current population is copied to the next population. By employing this procedure, the best solution is preserved from one population to the next.

In the proposed algorithm, we assume that each firefly estimates its brightness change before moving toward a better firefly. For this reason, initially, all better fireflies are identified and selected firefly moves toward them, implicitly. Then, brightness changes are calculated, and the best move is selected. After that, the firefly is moved toward better firefly that makes the best change, and the position of the moved firefly is updated. This way, we reduce the probability of generating worse solutions from one population to the next.

These steps are continued for other fireflies until initial positions of all members are changed. Now, the first iteration is achieved and the best solution of the new population is denoted. All former steps are repeated until stop criterion is met.

The pseudo code of the proposed SFA is illustrated as follows. To highlight the difference between proposed SFA and standard FA, the particular features of SFA are illustrated by gray color.

Begin

Generate fireflies for the initial population, randomly x_i $(i = 1, \dots, N)$

Calculate objective function $f(x_i)$, $x_i = (x_{i1}, \dots, x_{id})^T$

Consider $f(x_i)$ as brightness of firefly i (I_i)

Define light absorption coefficient (γ)

While (t<Max Generation)

For $i = 1 : N$

Find the firefly with the highest brightness in the current population

Exert a random movement on the current best firefly via $(\alpha \varepsilon_i)$

Calculate the firefly attractiveness after

movement via $\exp(-\gamma r^2)$
If ($I_{new} > I_{old}$), replace the moved firefly with current best firefly;
Transfer the moved firefly into the next population
Else Copy the current best firefly into the next population
End If
For $j = 1: N$
If ($I_j > I_i$), move firefly i towards firefly j in D dimension;
Calculate distance between fireflies i and j (r)
Calculate attractiveness via $\exp(-\gamma r^2)$
Obtain firefly i brightness and location after movement
Reserve the new brightness and new location of firefly i, Temporarily
Return the firefly i to the primal location
End If
End For j
Rank the brightness values obtained from several movements of firefly i
Select optimal movement
Record new location of firefly i
Record new brightness of firefly i
Update light intensity of firefly i
End For i
Rank the fireflies and find the current best
End While
Display process results and visualization
End

4-2. Penalty function

Applying the proposed meta-heuristic may generate infeasible solutions. To control the infeasible solutions, a penalty function is designed that takes zero for feasible solutions and a large positive value for infeasible solutions. The penalty function of a solution *x*, called $P(x)$, for a constraint $g(x) \leq b$ is calculated with use of Eq. 54 (47).

$$P(x) = R \times \max\left\{\frac{g(x)}{b} - 1, 0\right\}$$

where R is a large positive number. The penalty value is added to the objective function value.

4-3. The bi-objective feature

There are several methods, such as *Maxi-Min, LP-Metric*, *Weighting,* and *Lexicography*, to transform bi-objective models to single-objective form. One of the popular methods for transforming the bi-objective models with conflicting objectives to single objective is *LP-metric* (48), (49), (50). Therefore, in this paper, the LP-metric method is used to transform the proposed bi-objective problem to single-objective form.

The purpose of this method is to minimize the whole weighted deviations from the optimal value of each objective function. The following equation is applied to analyze the fitness of a solution (Eq. 55).

$$LP = \left[\sum_{j=1}^{k} \gamma_j \left(\frac{f_j^* - f_j}{f_j^*}\right)^p\right]^{\frac{1}{p}} \qquad (55)$$

where f_j and γ_j are the value and weight of the j^{th} objective, respectively. p is known as a control parameter with integer values equal to or greater than 1 (51). If $p = \infty$, the problem becomes the minimization of the maximal deviation (Eq. 56).

$$LP = \min\left\{\max\left\{\gamma_1\left(\frac{f_1^* - f_1}{f_1^*}\right), \gamma_2\left(\frac{f_2^* - f_2}{f_2^*}\right), \dots, \gamma_k\left(\frac{f_k^* - f_k}{f_k^*}\right)\right\}\right\} \qquad (56)$$

The problem can be presented as follows (Eq. 57-58).

$$Min\ v \qquad (57)$$

$s.t$:

$$v \geq \gamma_j\left(\frac{f_j^* - f_j}{f_j^*}\right), \quad \forall j \qquad (58)$$

5. Computational Experiments

To demonstrate the performance of SFA in solving the presented multi-stage PDN, several instances in different sizes are solved, and results of these algorithms are analyzed. Nine sets of small-sized and eight sets of large-sized instances are considered (table 1).

Tab. 1. Size of small and large instances

Instance no.	(I)	(J) no.	(K) no.	(D) no.	(C) no.	(C') no.	(Q) no.	(R) no.	(P) no.	(T) no.	No. of Parameters	No. of Variables
Small												
1	1	2	2	2	2	1	3	1	1	2	287	222
2	1	2	2	3	3	1	3	2	1	2	415	320
3	1	2	2	3	4	2	3	3	1	2	514	392
4	2	2	3	2	4	2	3	4	1	2	551	426
5	2	2	3	3	4	3	3	3	2	2	978	792
6	2	3	2	4	4	3	3	4	2	2	1047	860
7	2	2	3	4	5	3	3	3	2	2	1228	1000
8	2	3	3	4	5	3	3	4	2	2	1355	1118
9	3	3	2	4	5	3	3	3	2	3	1646	1431
Large												
1	3	3	3	3	6	3	3	3	3	3	2287	1953
2	3	3	4	3	6	4	3	3	3	3	2922	2505
3	3	4	4	3	5	3	3	4	3	3	3396	3000
4	4	5	4	4	5	3	3	3	4	3	4384	3960
5	3	4	5	3	6	3	3	4	4	3	5324	4800
6	4	5	3	4	6	5	3	3	5	3	5420	4870
7	3	4	4	5	7	4	3	3	5	3	6681	6045
8	4	5	5	5	7	5	3	4	6	3	12335	11418

Each type of small- and large-sized instances is solved five times, summing up to 85 instances. The parameters' values of both small- and large-sized problems with a concise description regarding generating the data range of each problem are presented in Table 2.

Tab. 2. Parameters' values for small and large sized instances

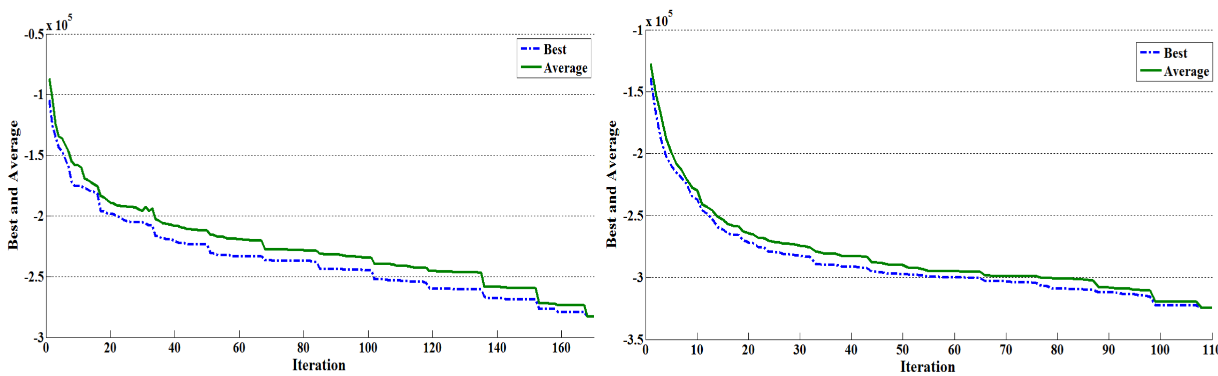
Parameter	Ranges of parameters		Description
	Small size	Large size	
$rtime_{jt}$	u~[1600, 3000]	u~[2800, 4800]	A data range of uniform distribution
$otime_{jt}$	u~[160, 300]	u~[280, 480]	10% of available regular time
pt_{jp} st_{jp} sc_{jpt} rp_{irt} rmc_{pt}	u~[4.0, 8.5] u~[18, 28] u~[80, 115] u~[2, 10] u~[4, 9]	u~[2.5, 8.0] u~[13, 25] u~[40, 150] u~[2, 9] u~[4, 11]	Randomly generated (uniform distribution)
omc_{pt}	u~[4.8, 10.8]	u~[5, 12]	120% of unit production cost at a regular time
$ltp_{jk}^{q} \sim N(\mu_{ltp_{jk}^{q}}, \sigma_{ltp_{jk}^{q}})$	N~(u[4, 12], u[1, 2])	N~(u[3,15], u[1,3])	A data range of uniform distribution for each normal distribution factor of lead time with respect to the type of transportation system
$ltp_{kd}^{\prime q} \sim N(\mu_{ltp_{kd}^{\prime q}}, \sigma_{ltp_{kd}^{\prime q}})$	N~(u[6, 15], u[2, 3])	N~(u[6, 18], u[2, 5])	
$ltp_{dc}^{\prime\prime q} \sim N(\mu_{ltp_{dc}^{\prime\prime q}}, \sigma_{ltp_{dc}^{\prime\prime q}})$	N~(u[10, 20], u[2, 4])	N~(u[8, 22], u[3, 6])	
$ltp_{kc'}^{\prime\prime\prime q} \sim N(\mu_{ltp_{kc'}^{\prime\prime\prime q}}, \sigma_{ltp_{kc'}^{\prime\prime\prime q}})$	N~(u[40, 80], u[3, 5])	N~(u[35, 90], u[4, 8])	
at	u~[20, 30]	u~[25, 35]	Randomly generated

at'	u~[55, 70]	u~[60, 80]	(uniform distribution)
$rftc_{ijt}$	u~[18, 30]	u~[10, 30]	Randomly generated (uniform distribution)
$rutc_{ijrt}$	u~[2, 5]	u~[2, 7]	
$pftc^{q}_{jkt}$	u~[20, 50]	u~[20, 50]	Randomly generated (uniform distribution) with respect to the type of transportation system
$putc^{q}_{jkpt}$	u~[3, 6]	u~[3, 15]	
$pftc'^{q}_{kdt}$	u~[25, 60]	u~[20, 55]	
$putc'^{q}_{kdpt}$	u~[2, 7]	u~[4, 16]	
$pftc''^{q}_{dct}$	u~[16, 60]	u~[15, 60]	
$putc''^{q}_{dcpt}$	u~[3, 8]	u~[5, 18]	
$pftc'''^{q}_{kc't}$	u~[45, 100]	u~[30, 80]	
$putc'''^{q}_{kc'pt}$	u~[8, 15]	u~[8, 22]	
vr_r	u~[0.4, 0.5]	u~[0.5, 1.0]	Randomly generated (uniform distribution)
vp_p	u~[1.0, 1.5]	u~[1.0, 1.5]	
$dem_{cpt} \sim N(\mu_{dem_{cpt}}, \sigma_{dem_{cpt}})$	N~(u[30, 55], u[3, 5])	N~(u[25, 65], u[5, 8])	A data range of uniform distribution for each normal distribution factor of inland and outland customers' demands
$dem'_{c'pt} \sim N(\mu'_{dem'_{c'pt}}, \sigma'_{dem'_{c'pt}})$	N~(u[140, 210], u[4, 6])	N~(u[120, 220], u[6, 8])	
hcr_{jrt}	u~[1.5, 7.0]	u~[1.5, 11.5]	Randomly generated (uniform distribution)
hcp_{jpt}	u~[3.5, 8.5]	u~[4.0, 9.5]	
hcp'_{dpt}	u~[5, 10]	u~[5, 13]	
nu_{rp}	u~[0, 2]	u~[0, 2]	
$capv$	u~[15, 20]	u~[15, 20]	
$capf_j$	u~[300, 450]	u~[300, 450]	
$capr_d$	u~[430, 550]	u~[430, 550]	
acc_{kt}	u~[35, 60]	u~[35, 80]	
pr_{cpt}	u~[1700, 2200]	u~[1900, 3500]	Randomly generated (uniform distribution) with respect to the time period
$pr'_{c'pt}$	u~[2100, 2700]	u~[2500, 4000]	
boc_{cpt}	u~[10, 20]	u~[10, 20]	With respect to priority of customers
$boc'_{c'pt}$	u~[5, 10]	u~[5, 10]	

In order to gain suitable results in several instances, the parameters of applied algorithms should be tuned. The FA and SFA parameters include population size (N_{pop}), step size scaling (α), light absorption coefficient (γ), and attractiveness (β). To optimize the performance of the algorithms, we consider a specified range for each parameter and solve several instances with regard to different values of each parameter. We apply *response surface methodology* (RSM) introduced by (52) to tune these parameters. The parameters in different sized instances in all considered algorithms are assumed with the same weight. MINITAB V.16.1.0 software is used to obtain the optimal values of FA and SFA parameters used to perform the numerical experiments. The optimal values of FA and SFA parameters obtained by using RSM are given in Table 3. The algorithms, FA and SFA, are coded in MATLAB R2013b v.8 2.0.70.1 and run on a Pentium IV 2.8 GHz processor with 4 GB memory. All considered algorithms are converged in specified iterations. The convergence charts of FA and SFA GA regarding a same problem are illustrated in Fig. 2 (a-b), respectively.

Tab. 3. Tuned parameters of FA and SFA

Instance no.	FA N_{pop}	FA α	FA γ	FA β	SFA N_{pop}	SFA α	SFA γ	SFA β
Small								
1	90.30	0.53	1.50	0.53	52.12	0.60	0.60	0.89
2	90.51	0.60	0.50	0.85	52.32	0.60	0.60	1.13
3	100.00	0.60	1.50	1.03	60.00	0.60	0.60	1.60
4	100.00	0.60	0.80	0.50	64.55	0.43	0.60	0.60
5	109.50	0.45	0.50	1.50	70.00	0.60	0.60	0.60
6	120.00	0.54	0.55	1.50	70.00	0.60	1.60	1.60
7	110.00	0.60	0.50	0.83	70.91	0.37	1.60	0.60
8	110.00	0.56	0.50	0.50	70.71	0.45	0.60	0.60
9	122.12	0.60	0.50	1.04	69.70	0.43	0.60	0.60
Large								
1	130.00	0.70	0.50	0.50	75.00	0.60	1.60	0.60
2	130.00	0.70	0.50	0.61	75.00	0.42	0.60	0.60
3	150.00	0.70	0.50	0.99	85.00	0.60	1.60	0.60
4	170.00	0.70	0.50	1.50	93.74	0.60	0.60	1.14
5	190.00	0.56	0.50	0.50	100.00	0.60	0.60	1.07
6	190.00	0.59	0.50	1.01	91.52	0.60	0.60	1.11
7	200.00	0.62	0.50	0.50	100.00	0.60	1.60	0.60
8	212.93	0.59	0.50	1.50	120.00	0.55	1.04	0.94



(a) FA **(b) SFA**

Fig. 2. The convergence charts of FA and SFA

To compare the effectiveness of the proposed algorithms, two indices including *relative percentage deviation* (RPD) and *improvement percentage* (IP) are used. To calculate RPD value for an objective function with minimization type, Eq. 59 is applied (1).

$$RPD = \frac{f_{sol} - f_{min}}{f_{min}} \times 100 \tag{59}$$

where f_{sol} and f_{min} are solution of the minimization objective function in bi-objective form and the optimal solution if the problem is solved in single-objective manner for a given instance, respectively.
The IP index is introduced by (34) to compare the performances of two algorithms. The IP formula is presented in Eq. 60.

$$IP_{min} = \frac{(Alg_{clas} - Alg_{pro})}{Alg_{pro}} \times 100 \tag{60}$$

where IP_{min} is improvement percentage of minimization objective function, and Alg_{pro} and Alg_{clas} are the proposed form of an algorithm and classical form of the algorithm, respectively.
Table 4 summarizes the consequences of experiments obtained by using each method for different small- and large-sized instances. The first part of the table shows RPD values obtained by using LINGO Global Solver. LINGO is able to solve small-sized instances in a reasonable amount of time (between 10 to 5000 seconds);

however, it is unable to obtain any feasible solutions after elapsing more than 5000 seconds in large-sized instances. Table 5 illustrates gained improvement in output of each objective function by using algorithm SFA. The average of IP gained with solving several small- and large-sized instances is presented in the last row.

Tab. 4. RPD values of small and large-sized instances

Instance no.	LINGO		FA		SFA	
	Min_{cost}	Min_{dltime}	Min_{cost}	Min_{dltime}	Min_{cost}	Min_{dltime}
Small						
1	7.03	25.48	19.80	33.01	14.96	22.09
2	12.09	10.36	40.98	34.19	40.94	21.36
3	10.28	25.27	22.06	76.22	20.78	53.68
4	8.77	20.46	19.58	67.82	17.48	50.26
5	10.77	25.31	9.80	55.48	9.13	50.43
6	50.20	18.71	9.54	60.97	7.73	52.73
7	10.65	27.43	5.89	56.74	8.39	44.12
8	9.34	21.80	13.16	55.04	7.04	49.83
9	18.50	16.72	7.56	70.65	3.63	60.55
Large						
1	-	-	3.22	47.70	4.10	18.92
2	-	-	2.88	52.76	0.56	21.47
3	-	-	6.03	47.64	4.60	25.93
4	-	-	17.87	31.35	15.53	24.77
5	-	-	20.08	30.71	13.92	25.16
6	-	-	19.55	45.86	18.97	39.30
7	-	-	22.68	61.82	22.40	49.24
8	-	-	21.32	60.59	21.55	47.37

Tab. 5. IP values gained from SFA

Instance no.	IP with using SFA		Mean of IP
	Min_{cost}	Min_{dltime}	
Small			
1	6.03%	8.94%	7.49%
2	0.08%	10.58%	5.33%
3	1.64%	14.67%	8.15%
4	2.61%	11.69%	7.15%
5	0.74%	3.35%	2.05%
6	2.00%	5.40%	3.70%
7	-2.66%	8.76%	3.05%
8	7.04%	3.47%	5.26%
9	4.24%	6.29%	5.27%
Large			
1	-0.91%	24.19%	11.64%
2	2.39%	25.76%	14.08%
3	1.53%	17.25%	9.39%
4	2.85%	5.27%	4.06%
5	7.70%	4.43%	6.07%
6	0.72%	4.71%	2.71%
7	0.36%	8.43%	4.39%
8	-0.29%	8.97%	4.34%
Average	2.12%	10.13%	6.12%

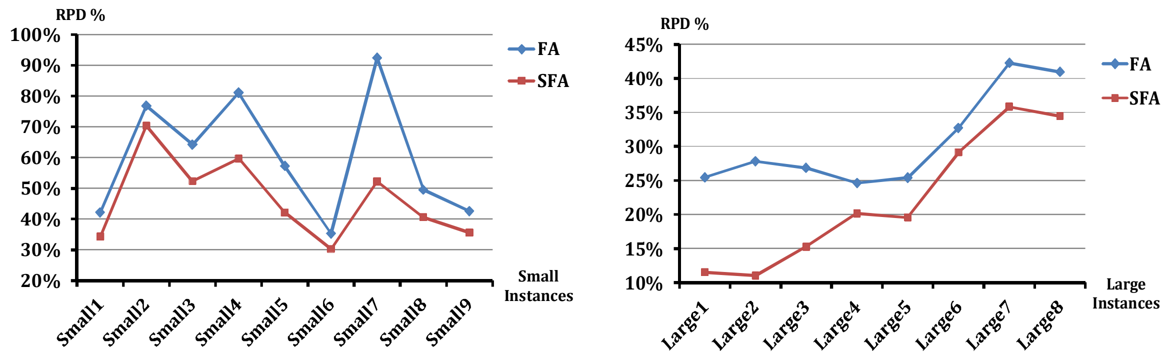
The results of the algorithms are analyzed by applying *t-test* with confidence level %95 by MINITAB V.16.1 software. The normality test is examined by Kolmogorov-Smirnov approach by MINITAB V.16.1 software. The equality of variances is examined. The hypothesis test of algorithms FA and SFA is as follows.

$$\begin{Bmatrix} h_0: \mu_{FA} = \mu_{SFA} \\ h_a: \mu_{FA} \neq \mu_{SFA} \end{Bmatrix}$$

where μ_{FA}, μ_{SFA} are the average RPD values of FA and SFA, respectively.

In accordance with the results gained from the dependent *t*-test (comparing FA and SFA), *t value* and *p value* are calculated as 1.73 and 0.047, respectively. Regarding the obtained values of *p value* in the *t*-test as lower than 0.050 and *t value* greater than $t_{0.95,35}$, null hypotheses of two t tests are rejected with %95 confidence level. It proves the significant difference between RPD values obtained from different algorithms.

Fig. 3 illustrates the average RPD of two objective functions (Min_{cost} and Min_{dltime}) related to several problems. In both small- and large-sized instances, quality improvement of solutions with applying SFA is sensible in most cases. Therefore, for solving these types of mathematical models specially, in large-sized instances, applying SFA instead of classical FA can be useful to achieve better solutions.



(a) Small-sized instances **(b) Large-sized instances**

Fig. 3. Integrated RPD values of FA and SFA

6. Conclusion

This paper investigated a comprehensive international PDN with multiple potential entrepots for collecting and transferring the products to retailers and customers. There are multiple transportation systems with different delivery lead times. Therefore, it can be applicable for industries that have several products with different sensitivities. The problem was formulated as a MILP model. The customers' demands and delivery lead time in the proposed network were assumed under uncertainty with stochastic form. Chance-constraint technique was applied to convert the probabilistic model to deterministic form. To investigate the performance of the proposed model, several sized instances were designed, and a novel proposed algorithm based on FA called SFA was introduced to solve the model. In the proposed SFA, each fire fly handles a selective procedure before moving toward better fire flies. It means that each fire fly selects several fire flies and predicts its next position after moving and, then, selects the best firefly that makes the most improvement. The results show the improvement the performance of the proposed algorithm as compared to the classical form.

As a direction for future research, it could be interesting to develop other metaheuristic methods and compare them with SFA. Another aspect of this research could be considering discount depending on the quantity of customers' orders. In addition, a separate objective function to minimize the greenhouse gases omission through the network can be utilized in the future researches.

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