Hybrid optimizers to solve a tri-level programming model for a tire closed-loop supply chain network design problem

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Graphical abstract

The scraped tires may be left in nature to pollute the environment (this photo is taken from our case study)

The graphical structure of tire closed-loop supply chain

Highlights

- Designing a tri-level programming model for the tire closed-loop supply chain;
- Proposing four new hybrid optimizers to improve the recent and old used meta-heuristics in an efficient way;
- Comparing the hybrid algorithms with their general ideas by a set of comprehensive analyses;
- Demonstrating the benefits of the proposed methodology using a real case study and sensitivity analyses;
- Among these hybrid methods, HKASA shows the best performance in practice.

Abstract

The Closed-loop Supply Chain (CLSC) is one way to collect and recycle scraped tires. CLSC consists of a set of suppliers, manufacturers, distributors and customers in a forward system. Collectors and recyclers are formed a reverse one as well. The decisions in such systems are adopted in a hierarchy.

Regarding this issue, this study develops a tri-level programming model to design the location-allocation of the tire CLSC for the first time. The proposed model is formulated on the static *Stackelberg* game between manufacturers, distributors and collectors in the framework of CLSC. The performance of the current exact solutions for this problem suffers from degraded performance when solving large-scale problems. To alleviate this drawback, this study proposes a number of new hybrid optimizers by considering the benefits of recent metaheuristics. An extensive comparative study confirms the efficiency of developed model and the performance of the hybrid optimizers proposed when solving the large-scale problems.

Keywords: hybrid optimizers; metaheuristic algorithms; tri-level programming; location-allocation problem; tire closed-loop supply chain;

1.Introduction and literature review

In the recent years, there has been an increasing interest in terms of Closed-Loop Supply Chain (CLSC). The profits of collecting and recycling the products lead to investigate the Reverse Logistic (RL) and CLSC systems [1]. The main operation in the CLSC is considered as the location of facilities and allocation of different parts of a system [2]. In such systems, the management is determined by different levels (*e.g.* manufacturers and distributors in the forward system and collectors in the reverse ones) [3]. All parts of a supply chain act in a cooperative manner to decide the best strategy [4]. The behavior of each level is adopted according to its benefit and the best strategy should be selected [5]. In this way, the multi-level programming is an efficient tool to simulate such systems [6]. In this work, a tri-level location-allocation model is designed for tire CLSC. Accordingly, the manufacturers are the first level, distributors form the second level and collectors guaranty the returned scraped tires in the reverse loop as the third level. The motivation of presented tire closed-loop supply chain is addressed by the following sub-section.

1.1. Motivation

There are more than one billion brands for tire in the world with nearly 500 producers across the globe [7]. According to the report of the U.S. Environmental Protection Agency (EPA), each U.S. family has three cars that used 24 tires every 3 years. As such, approximately 290 million scraped tires are disposed every year of which 20% are illegally scraped in landfills or roadsides.

This causes an important disposal problem with health hazard and environmental damages [8]; [9]. In addition, the chemicals leached from the scraped tires are hazardous for human health, water and air pollution [7]. Unfortunately, in major cases, the scraped tires are released in the nature without considering the affection on environments. Figure 1 shows an example, in which thousands of scraped tires contaminate the nature of jungles in northern regions of Iran.

Tire recycling is a process of converting scraped tires into material that can be utilized again for manufacturing [10]. Tire recycling has gained much attention in recent years by government across the globe. For instance, Chopra and Meindle [11] discussed in 2015 that in U.S. only three percent of scraped tires are recycling between 2009 and 2011. Overall, it shows the importance of recycling for the scraped tires.

1.2. Tire closed-loop supply chain

In the literature of CLSC and RL methodologies, there are several articles in this area of which only a few papers review the related studies and suggest future works (See [12] [13] [14] [15]).

In the area of tire supply chain, less than ten studies have been published despite its importance. In 1997, Ferrer [16] estimated the optimal number of times which the tires can be reused. In 2009, the mathematical model to probe the tire supply chain was introduced by Kannan *et al.* [17]. They developed a CLSC system for tires and plastic via a Mixed Integer Linear Programming (MILP). In addition, an RL system for the tire supply chain was addressed by Sasikumar *et al.* [18] in 2010 for truck tire remanufacturing process. In another seminal research, Subulan *et al.* [7] introduced a case study in Turkey to investigate this issue. They used a Fuzzy Mixed Integer Programming (FMIP) by a fuzzy solution approach to address their CLSC optimization model. In the top of the most recent works, Amin *et al.* [10] developed an economic optimization model for tire CLSC under uncertainty conditions in Toronto, Canada. In this paper, a tri-level programming model was used to simulate the decision levels for tire CLSC by a real data set.

Overall, it is evident that the application of such models should be examined in a real case study to achieve the managerial implications of tire supply chain. This reason motivated several works including the current work to use a real case study. Another main similarity of mentioned studies is referred to considering the RL operations in an efficient way to ease the managing of such systems [2]. Unlike the past studies, this study proposes a tri-level programming model to

reach this goal more efficiently. It has been proven that a multi-level programming gives a performance tool to manipulate the RL and CLSC operations [19].

In our proposed system, manufacturers can purchase raw material from suppliers and recyclers. Distributors as the middle-level buy the different types of tires from manufacturers and sell them to markets. Finally, collectors as the bottom-level collect the scraped tires from customers and prepare them for recycling centers. Figure 2 shows the graphical structure of the proposed tire CLSC model.

1.3. Multi-level programming for location-allocation problem

Multi-level programming or multi-level decision-making is a kind of hierarchical optimization problem. This type of optimization model is used in many applications especially for location-allocation problems [19]. The simplest case of multi-level programming is bi-level. In this method, the objective function of lower-level forms a constraint of upper-level model. The bi-level programming is formulated on the game theory of Stackelberg [20]. This type of model was presented by Bracken and McGill [21] for the first time. They defined the bi-level programming as a "*mathematical program with optimization in the constraint*". As pointed out by Ben-Ayed [22], bi-level models are difficult to solve in any sizes. The easiest case of a bi-level model is obviously hard and known as NP-hard. Due to the degraded performance of exact methods when solving this NP-hard problem, various heuristics and metaheuristics have been developed in the literature [5].

Up to our knowledge, the location-allocation problem was first modeled by Taniguchi *et al.* [23] using bi-level programming. They proposed a capacitated location-allocation of cross-docking system. A Genetic Algorithm (GA) was employed in their work to solve the non-linear upper level model. Huang and Liu [24] also used GA to solve the two-stage supply chain model with balanced workload requirement for the lower level. Generally, regarding the literature, there are also some other works utilizing the multi-level programming to formulate the location-allocation problem. For instance, a hybrid of GA and Particle Swarm Optimization (PSO) was considered by Kuo and Han [25] to solve the underlying bi-level location-allocation model. Ma *et al.* [26] developed a bi-level model in which the upper level was manufacturers and the retailers formed the lower-level problem. They also used PSO to solve their model. In 2014, Zhang and Xu [27] added the demand uncertainty and continued cost function for the lower-level

in their proposed bi-level programming model. They employed a heuristic-based GA to address the model. In 2016, one of interesting works in the literature was conducted by Saranwong and Likasiri [28], in which the location-location problem, which considered the distributors as the upper-level and customers in the lower-level, was proposed. They solved the model with five heuristic algorithms and verified the performance of model through a real case study. In a similar study, the same authors explored the Thailand's sugarcane management by a bi-level programming approach [29].

In 2017, Parvasi *et al.* [30] proposed a bi-level programming model for a location-allocation-routing problem for content of public transportation systems with possibility of outsourcing demand. They also used GA and SA to solve their bi-level model. Recently, Fathollahi Fard and Hajaghaei-Keshteli [19] proposed a tri-level location-allocation model for forward/reverse supply chain network design problem. They approved the application of their model in glass industry through a case study in Iran. They employed five metaheuristics including Tabu Search (TS), Variable Neighborhood Search (VNS), PSO, Keshtel Algorithm (KA) and Water Wave Optimization (WWO) to solve the problem.

Taken together, the mentioned studies revealed that metaheuristics are effective approaches to solve the underlying multi-level programming model for location and allocation problem. The literature showed that using hybrid algorithms is still scarce in this area [4]. Additionally, the No Free Lunch theorem [31] states that there is no optimization algorithm to solve all optimization problems. Therefore, the current algorithms might need modifications, tunings, or hybridizations to solve a set of specific problems [32]. These drawbacks motivate us to attempt a set of new hybrid optimizers as the main contributions of this study.

1.4. Highlights and contributions

Generally speaking, the aforementioned studies in this area can be divided into three categories: improving optimization model, improving current solution approaches or suggesting new optimizers, and improving both model and solution algorithms. CLSC may be formulated and modeled with different assumptions and considering more factors [33]. Although adding more elements makes CLSC more practical, it increases the difficulty and computation cost of this problem [34]; [35]. This means that changing case model and/or case study will change the search space of the problem and might result in getting poor results using the current optimizers

[36]. These facts keep this area active and motivate our attempts to contribute to both areas: a new optimization model along with optimizer improvement by four new hybrid metaheuristics.

To cope with the described problem as illustrated in the last three sub-sections, this study proposes a tri-level location-allocation model for tire closed-loop supply chain. One of the advantages of this technique is to decide the best strategy for the main level for location and allocation of facilities [4]. To the best of our knowledge, this study is the first attempt to consider a closed-loop supply chain for tire products. In 2018, Fathollahi Fard and Hajaghaei-Keshteli [19] proposed a tri-level programming model for a forward/reverse supply chain, but this study considers a tire CLSC for the first time by a tri-level programming approach. Another main contribution of this study in comparison with other similar papers is to propose four new hybrid optimizers based on recent and old metaheuristics. As mentioned earlier, in the developed model, manufacturers, distributors and collectors are formed the three main decision makers for the tire closed-loop supply chain which considers as the first, second and third levels of offered model, respectively. The main contributions of this study can be outlined as follows:

- Developing a tri-level programming model for tire closed-loop supply chain for the first time.
- Applying a nested approach, namely, tri-level metaheuristic, to solve the underlying tri-level model.
- Keshtel Algorithm (KA) [37] and Stochastic Fractal Search (SFS) [38] (as recent metaheuristics), Simulated Annealing (SA) [39] and Variable Neighborhood Search (VNS) [40] (as the conventional optimization algorithms, and four hybrid optimizers are evaluated.
- Comparing the results of the hybrid meta-heuristics with general ideas through different criteria in the terms of hitting time (the first time that algorithms find the best solution), solution quality, convergence of algorithms and time consumption.
- Validation of the proposed methodology by sensitivity analyses through a real case study.

The rest of the paper is organized as follows. Section 2 illustrates the problem description and model formulation. In Section 3, the solution approaches with illustration of proposed hybrid optimizers are given. In Section 4, the experimental results of algorithms are represented by a

comprehensive evaluation in different criteria. Finally, the conclusion and future works are discussed in Section 5.

2. Proposed problem

In this section, we consider the multi-level tire closed-loop supply chain including suppliers, manufacturers, distributors, customers, collectors, and recyclers. A manufacturer supplies the raw material of tires from suppliers and recyclers. Then, manufactured tires are distributed in market by distributors. Collectors collect a part of the scraped tires that were used by customers in markets and send to recycling facilities. After recycling, the recycled material can be sent back to tire supply chain for remanufacturing. The CLSC problem covers both forward flow (*i.e.* from supplier to market) and reverse flow (*i.e.* from market to manufacturer or recycler). The tire closed-loop supply chain network is shown in Figure 2. A tri-level programming is employed to formulate the tire closed-loop supply chain. The structure of tri-level model is depicted in Figure 3. As can be seen, the manufacturers, distributors and collectors are the decision levels for the developed tri-level model. The suppliers, recyclers and markets are fixed. For each decision level, we want to optimize the location of facilities and allocation of products. In the next subsection, the characteristics of the problem are illustrated.

2.1. Problem description

This study aims to tackle the location-allocation problem for designing the tire closed-loop supply chain by considering three decision levels to select an optimized strategy for each level. The proposed problem is a multi-echelon, multi-product with multiple nodes among echelons as shown in Figure 2. Each facility of supply chain can be opened in a potential location with specific opening fixed cost ($FC_{\square}^{\square}$), variable cost ($MC_{\square}^{\square}$), holding cost ($H_{\square}^{\square}$), purchasing cost ($PC_{\square}^{\square}$), maximum number of each facility per level ($MAX_{\square}$), storage capacity ($CAP_{\square}^{\square}$), safety stock ($S_{\square}^{\square}$) and transportation cost between other facilities ($TC_{\square}^{\square}$). For example, the fixed, variable and holding costs for opening manufacturing plant in the potential location m with a storage capacity CAP_{mp}^M and safety stock S_{mp}^M (regarding the type of tire p) are considered by FC_m^M , MC_{mp}^M and H_{mp}^M respectively. In addition, transportation costs have been considered by TC_{im}^I for transporting the raw materials between suppliers and manufacturers two different echelons. Similarly, the transportation cost of product p between manufacturer plant m and

distributor center j is TC_{mjp}^M . Manufacturer (m) can supply the raw material from supplier (i) or recycler (r) with different price PC_i^I or PC_r^R . The distributor (j) purchase the tire type p from the manufacturer m with price PC_{mp}^M and distribute in market (l) with price PC_{jp}^J according to the markets' demand d_{lp} which has been generated by a normal distribution function ($N(d_{lp}^\mu, d_{lp}^\delta)$). In the reverse flow, however, the potential collector center (n) collect α_{lp} percentages of the scraped tires (p) with price PC_{lp}^L from market (l). This fraction of returned products has been estimated by a normal distribution function ($\alpha_{lp} \sim N(\alpha_{lp}^\mu, \alpha_{lp}^\delta)$). The potential recycler plant location (r) purchases the scraped tire type (p) from collector (n) with price (PC_{np}^N) and sell to potential manufacturing/remanufacturing plant with price PC_r^R . Overall, the proposed model aims to determine the locations of the facilities and the right allocations in the forward and reverse flows of tire closed-loop supply chain by considering a tri-level programming model as the framework.

2.2. Assumptions

The problem investigated in this work is addressed considering the following assumptions:

- This model considers a multi-product, single period, and multiple facilities in a closed-loop supply chain.
- Only manufacturers, distributors and collectors can decide their strategies to be optimized. These levels are the decision levels of CLSC in the presented model. The rest of them are fixed.
- Regarding each decision level, the fixed and variable cost, transportation cost, production cost and holding cost are considered to be optimized.
- The demand of each customer must be met.
- Each facility may be assigned to more than one facility.
- The location of facilities should be determined regarding the optimal solution in each level.
- There is no flow between the same facilities in each level.
- The capacity of each facility in each location is limited and related to the demand.

- As a supposition assumption from Devika *et al.* [1], a part of distributed tires in markets must be collected after utilization as scrapped tires.
- To consider the uncertainty of demand of markets along with the quantity of returned tires, a normal distribution function is used to estimate them [14].
- The raw material price of the recyclers is less than supplier.

2.3. Notations

The indices, parameters and variables used to mathematically formulate the problem are described below.

Indices:

i	Index of suppliers, $i \in \{1, 2, \dots, I\}$
m	Index of potential manufacturing plant location, $m \in \{1, 2, \dots, M\}$
j	Index of potential distribution center location, $j \in \{1, 2, \dots, J\}$
l	Index of market zones, $l \in \{1, 2, \dots, L\}$
n	Index of potential collecting center location, $n \in \{1, 2, \dots, N\}$
r	Index of recycler, $r \in \{1, 2, \dots, R\}$
p	Index of tire type : $p \in \{1, 2, \dots, P\}$

Parameters:

TC_{im}^I	Transportation cost per unit form supplier i and manufacturer m
TC_{mjp}^M	Transportation cost per unit for tire type p from manufacturer m and distributor j
TC_{jlp}^J	Transportation cost per unit for tire type p from distributor j and market l
TC_{lnp}^L	Transportation cost per unit for tire type p form market l and collector n
TC_{nrp}^N	Transportation cost per unit for tire type p form collector n and recycler r
TC_{rm}^R	Transportation cost per unit form recycler r and manufacturer m
FC_m^M	Fixed opening cost of manufacturer m to be established
FC_j^J	Fixed opening cost of distributor j to be established
FC_n^N	Fixed opening cost of collector n to be established
MC_{mp}^M	Variable manufacturing cost per unit for tire type p and manufacturer m
MC_{jp}^J	Variable distributing cost per unit for tire type p and distributor j
MC_{np}^N	Variable collecting cost per unit for tire type p and collector n
PC_i^I	Cost of purchasing raw material for all types of tires for supplier i
PC_{mp}^M	Cost of purchasing tire type p for manufacturer m
PC_{lp}^L	Cost of purchasing tire type p for market l
PC_{jp}^J	Cost of purchasing tire type p for distributor j

PC_{np}^N	Cost of purchasing tire type p for collector n
PC_r^R	Cost of purchasing recycled tires for all types of tires from recycler r
H_{mp}^M	Holding cost of returned and produced tires per unit tire type p at manufacturers
H_{np}^N	Holding cost of collected the scraped tires per unit tire type p by collectors
H_{jp}^J	Holding cost of produced tires for distributing per unit tire type p at distributors
MAX_m	Maximum desired number of established sites for manufacturers
MAX_j	Maximum desired number of established sites for distributors
MAX_n	Maximum desired number of established sites for collectors
$d_{lp} \sim N(d_{lp}^\mu, d_{lp}^\delta)$	Normal distributed demand of market l for tire type p
d_{lp}^μ	Mean value of demand of market l for tire type p
d_{lp}^δ	Variance value of demand of market l for tire type p
$\alpha_{lp} \sim N(\alpha_{lp}^\mu, \alpha_{lp}^\delta)$	Normal distribution for the fraction of used tires type p returned from market l .
α_{lp}^μ	Mean value of the fraction of used tires type p returned from market l
α_{lp}^δ	Variance value of the fraction of used tires type p returned from market l
CAP_i^I	Storage capacity of supplier i
CAP_{mp}^M	Storage capacity of manufacturer m for tire type p
CAP_{jp}^J	Storage capacity of distributor j for tire type p
CAP_{np}^N	Storage capacity of collector n for tire type p
CAP_{rp}^R	Storage capacity of recycler r for tire type p
S_{mp}^M	Safety stock of manufactured tire type p at manufacturer m
S_{np}^N	Safety stock of collected tire type p at collector m
S_i^I	Safety stock of supplier i
S_{jp}^J	Safety stock of tire type p at distributor j
S_{rp}^R	Safety stock of recycled tire type p at recycler r
Decision variables:	
X_{im}^I	Amount of products flow between supplier i and manufacturer m
X_{rm}^R	Amount of products flow between recycler r and manufacturer m
X_{mjp}^M	Amount of tires type p transformed between manufacturer m and distributor j
X_{jlp}^J	Amount of tires type p transformed between distributor j and market l
X_{lnp}^L	Amount of returned tires type p transformed between market l and collector n
X_{nrp}^N	Amount of reused tires type p transformed between collector n and recycler r
Y_m^M	1 if manufacturer m is to be established, otherwise 0
Y_j^J	1 if distributor j is to be established, otherwise 0

Y_n^N 1 if collector n is to be established, otherwise 0

2.4. Mathematical formulation

Regarding the proposed mathematical formulation, manufacturers (MNs) are the top-level, distributors (DCs) are the middle-level, and the collectors (COs) are the bottom-level in the framework of tire CLSC. Here, the proposed tri-level programming model is addressed as follows:

$$MN : \min Z_1 = \sum_{m=1}^M Y_m^M \times FC_m^M + \sum_{i=1}^I \sum_{m=1}^M (TC_{im}^I + PC_i^I) \times X_{im}^I + \sum_{r=1}^R \sum_{m=1}^M (TC_{rm}^R + PC_r^R) \times X_{rm}^R \quad (1)$$

$$+ \sum_{m=1}^M \sum_{p=1}^P \sum_{j=1}^J (MC_{mp}^M - PC_{mp}^M) \times X_{mjp}^M + \sum_{m=1}^M \sum_{p=1}^P H_{mp}^M \times \sum_{l=1}^L \frac{S_{mp}^M - d_{lp}^\mu}{d_{lp}^\delta} \times \sqrt{\sum_{j=1}^J (X_{mjp}^M \times d_{lp}^\delta)^2}$$

$$s.t. \sum_{m=1}^M Y_m^M \leq MAX_m \quad (2)$$

$$\sum_{r=1}^R X_{rm}^R + \sum_{i=1}^I X_{im}^I = \sum_{j=1}^J \sum_{p=1}^P X_{mjp}^M, \forall m \quad (3)$$

$$\sum_{m=1}^M X_{im}^I + S_i^I \leq CAP_i^I, \forall i \quad (4)$$

$$\sum_{m=1}^M X_{rm}^R + \sum_{p=1}^P S_{rp}^R \leq \sum_{p=1}^P CAP_{rp}^R, \forall r \quad (5)$$

$$\sum_{j=1}^J X_{mjp}^M + S_{mp}^M \times Y_m^M \leq Y_m^M \times CAP_{mp}^M, \forall m, p \quad (6)$$

$$Y_m^M = \{0, 1\} \quad (7)$$

$$X_{im}^I, X_{rm}^R \geq 0 \quad (8)$$

where X_{mjp}^M is solved by the following level (second level):

$$DC : \min Z_2 = \sum_{j=1}^J Y_j^J \times FC_j^J + \sum_{m=1}^M \sum_{j=1}^J \sum_{p=1}^P (TC_{mjp}^M + PC_{mp}^M) \times X_{mjp}^M + \sum_{j=1}^J \sum_{l=1}^L \sum_{p=1}^P (TC_{jlp}^J - PC_{jp}^J) \times X_{jlp}^J \quad (9)$$

$$+ \sum_{j=1}^J \sum_{l=1}^L \sum_{p=1}^P MC_{jp}^J \times X_{jlp}^J + \sum_{j=1}^J \sum_{p=1}^P H_{jp}^J \times \sum_{l=1}^L \frac{S_{jp}^J - d_{lp}^\mu}{d_{lp}^\delta} \times \sqrt{\sum_{l=1}^L (X_{jlp}^J \times d_{lp}^\delta)^2}$$

$$s.t. \sum_{j=1}^J Y_j^J \leq MAX_j \quad (10)$$

$$\sum_{m=1}^M X_{mjp}^M = \sum_{l=1}^L X_{jlp}^J, \forall j, p \quad (11)$$

$$\sum_{j=1}^J X_{jlp}^J \leq d_{lp}, \forall l, p \quad (12)$$

$$\sum_{l=1}^L X_{jlp}^J + Y_j^J \times S_{jp}^J \leq Y_j^J \times CAP_{jp}^J, \forall j, p \quad (13)$$

$$\sum_{n=1}^N X_{lnp}^L \leq a_{lp} \times d_{lp}, \forall l, p \quad (14)$$

$$Y_j^J = \{0, 1\} \quad (15)$$

$$X_{mjp}^M, X_{jlp}^J \geq 0 \quad (16)$$

where X_{lnp}^L is solved by the following level (third level):

$$CO: \min Z_3 = \sum_{n=1}^N Y_n^N \times FC_n^N + \sum_{l=1}^L \sum_{n=1}^N \sum_{p=1}^P (TC_{lnp}^L + PC_{lp}^L) \times X_{lnp}^L + \sum_{n=1}^N \sum_{r=1}^R \sum_{p=1}^P TC_{nrp}^N \times X_{nrp}^N \quad (17)$$

$$+ \sum_{n=1}^N \sum_{p=1}^P \sum_{r=1}^R (MC_{nrp}^N - PC_{nrp}^N) \times X_{nrp}^N + \sum_{n=1}^N \sum_{p=1}^P H_{np}^N \times \sum_{l=1}^L \frac{S_{np}^N - \alpha_{lp}^\mu \times d_{lp}^\mu}{\alpha_{lp}^\delta \times d_{lp}^\delta} \times \sqrt{\sum_{r=1}^R (X_{nrp}^N \times \alpha_{lp}^\delta \times d_{lp}^\delta)^2}$$

$$s.t. \sum_{n=1}^N Y_n^N \leq MAX_n \quad (18)$$

$$\sum_{l=1}^L X_{lnp}^L + Y_n^N \times S_{np}^N \leq Y_n^N \times CAP_{np}^N, \forall n, p \quad (19)$$

$$\sum_{l=1}^L X_{lnp}^L = \sum_{r=1}^R X_{nrp}^N, \forall n, p \quad (20)$$

$$\sum_{n=1}^N X_{nrp}^N + S_{rp}^R \leq CAP_{rp}^R, \forall r, p \quad (21)$$

$$Y_n^N = \{0, 1\} \quad (22)$$

$$X_{lnp}^L, X_{nrp}^N \geq 0 \quad (23)$$

As can be seen from the developed tri-level programming model, the equations (1) to (8) represent the first level for MNs' decisions. The equations (9) to (16) demonstrate the DCs' decision. Finally, the equations (17) to (23) indicate the decision level of COs.

From the first level, i.e. manufacturers (MNs), the objective function is represented in the equation (1). The first term determines the fixed opening cost regarding the locations of potential facilities for MNs. The second and third terms compute the transportation cost and purchasing cost for received raw materials from suppliers and or recyclers, respectively. Regarding the production costs, the manufacturing costs introducing the variable cost for manufacturing plants along with the profit of sold tires to distributors are considered, respectively. Finally, the holding cost or the storage cost is incurred due to inventory of manufactured and remanufactured tires. The last term is the sum of holding cost of manufacturers by ensuring that the safety stock can satisfy the corresponding demands.

The constraints of first level decision-making are presented by equations (2) to (8). Equation (2) shows the budget related to the maximum number of located facilities for the MNs. Equation (3) represents the flow of products between two different echelons. It means that the sum of raw materials from suppliers and recyclers should be equaled to the amount of manufactured tires distributed from MNs to DCs. The equations (4) to (6) show the maximum storage capacity of suppliers, recyclers, and MNs along with their safety stocks, respectively. The last two equations ensure the feasible amount of decision variables for the first level i.e. MNs.

The second level is to choose the DCs decisions. As such, the equation (9) is the objective function to minimize the total cost for DCs, and the equations (10) to (16) are the related constraints for the middle-level i.e. DCs. Regarding the objective function of this level, the first item aims to calculate the fixed opening cost corresponding to the location of DCs. The second term represents the transportation cost and purchasing cost for transformed tires between the manufacturers to DCs. The third one calculates the transportation cost and the profits of sold tires to customers. Similarly, the fourth term shows the variable cost of distributing the tires to customers. Finally, the last term reveals the holding cost of distributors by controlling the safety stock which can satisfy the corresponding demands.

Regarding the constraints, the equation (10) illustrates the predefined maximum number of located DCs. The equation (11) reveals that all manufactured tires should be distributed among customers. Similarly, the equation (12) shows that all demand of customers should be met by DCs, as well. The equation (13) states that the flow of products through a DC is allowed only the DC is open and has enough storage capacity and safety stock as well. Furthermore, the equation (14) shows the amount of returned tires which should be collected by collectors (COs) is limited

by a fraction of customer's demand. The last constraint of the second level refers the decision variables of DCs which are guaranteed by the equations (15) and (16).

The third level determined by COs maintains the reverse flows of used tires. The equation (17) considers the objective function of this level in five items. The first one shows the location decisions by calculating the fixed opening cost of facilities. The transportation cost and purchasing cost to collect the tires from markets and to transform them into recycling centers are considered by the second and third terms, respectively. The fourth item represents the variable cost for collecting of scraped tires along with the profits of COs from selling these collected tires to recyclers, as well. Eventually, the five item of objective function aims to calculate the holding cost of collectors by controlling the safety stock which can satisfy the corresponding demands of returned products.

From the constraints of COs level, the equation (18) by considering the fixed opening costs of COs, limits the number of established ones. Furthermore, the flow of collected scraped tires through a CO is allowed only that this facility must be opened and has enough storage capacity along with safety stock as can be seen from equation (19). Regarding the flow of returned products, the equation (20) shows that all collected tires should be recycled, as well. Equation (21) reveals the limitation of storage capacity and safety stock for recyclers. Finally, the equations (22) and (23) ensure the feasible amounts of decision variables of COs.

3. Solution approach

As mentioned earlier, the multi-level programming is NP-hard. Several approaches have been proposed to solve the bi-level and tri-level models. The solution methods for bi-level programming models can be divided into three classes [5]. The first category includes vertex enumeration methods [41]; [42]; [43]. The second classification is called Kuhn-Tucker algorithm [42]; [44]; [45]. In the last classification, penalty functions are used to tackle the bi-level programming models [46]. Hybridizing metaheuristics with explicit enumeration method has been done by Aksen and Nectai [47]. They utilized TS to solve the upper-level model and the solutions in the lower were validated by explicit enumeration method. Finally, an integrated approach by using metaheuristic was mentioned in the book written by Talbi [48]. The aim of this book was to introduce different metaheuristics including GA, PSO, TS and Differential Evolution (DE) [49] for solving the bi-level programming models.

Some works that use tri-level models are: cutting plane algorithm [50], penalty function approach [51], Kuhn-Tucker transformation method [52], multi-parametric programming approach [53] and tri-level K th-best algorithm [54]. The main drawback of such method is the poor performance when applying to high-dimensional case studies. To alleviate this limitation, heuristics techniques have been used in the literature. For instance, Mahmoodjanloo *et al.* [55] proposed two hybrid approaches based on the exact and metaheuristics. In their tri-level model, the first level was solved by a metaheuristic. The second level was evaluated by explicit enumeration algorithm and an exact approach was utilized for the third-level. In 2016, Han *et al.* [6] solved the tri-level programming model by PSO utilizing Kuhn-Tucker method for the lower levels as another method by hybridizing exact and metaheuristic solvers, simultaneously. Recently, Fathollahi Fard and Hajaghaei-Keshteli [19] introduced tri-level metaheuristic for solving the tri-level programming models for the first time.

In this work, we apply a simple nested approach called tri-level metaheuristic which uses metaheuristics for all levels to tackle the proposed tri-level programming model as well. We use SA and VNS as the popular metaheuristics existing in the literature along with KA and SFS as the two recent nature-inspired optimizers. The descriptions of these four algorithms are given in Supplementary Materials (F1). In addition, the main contribution of this study is to develop four new hybrid optimizers based on the benefits of recent and traditional metaheuristics. In the following, the structure of the proposed model and the process of solving it using a tri-level metaheuristic are discussed.

3.1. Tri-level metaheuristic to solve the proposed tri-level mathematical model

In multi-level programming, the variable of upper-level is the parameter in the lower-level. It means that all levels have a full knowledge about each other. The proposed multi-level model is a tri-level one. In this case, the first level is the leader and the two other levels are the followers. The proposed solution approach based on the developed tri-level mathematical model has been depicted by Figure 4. Accordingly, the considered model can be summarized as the following equations:

As mentioned earlier, Talbi [48] proposed a nested approach to solve the bi-level model in which both levels are solved by metaheuristics. Fathollahi Fard and Hajaghaei-Keshteli [19] proposed a similar approach named tri-level metaheuristic. In this approach, the first level is first solved by metaheuristic approach using random solutions from lower levels. Then, the solution for this level is sent to the middle-level to solve the second one. These procedures are repeated for the third level. In the next iteration, the solution for lower level is sent back to upper level and the upper-level is resolved and this procedure will be continued [5]. Figure 4 shows the flowchart of the tri-level metaheuristic for the proposed tri-level model. It should be noted, according to Talbi [48], each level can be solved by only metaheuristic. In this paper, all levels are solved by the same metaheuristic to compare the methods.

3.2. Encoding plan

It is evident that, an encoding plan is needed to implement the employed algorithms when solving a discrete formulation by metaheuristics [5]. As such, a two-stage technique is utilized to set the problem for metaheuristics. Random-Key (RK) is a popular technique for representing a solution from a uniform distribution to a discrete one [56]. In RK, a solution is first created by random numbers. This solution can be used in a search space by various operators [57]. It is then converted to a feasible discrete problem by a procedure as illustrated here. This technique was utilized in several related papers to encode the mathematical models ([58][59][56][57] [2]).

In Figure 5, the proposed encoding method is shown. It can be seen that the solution is divided into two sub-solutions. Figure 5(a) shows the encoding plan for binary variables [3]. This sub-solution chooses the location of potential facilities for each level. Figure 5(b) depicts a priority-based representation to assign the facilities from different levels together. Regarding the literature, Gen *et al.* [60] proposed the priority-based representation in a two-stage transportation problem. This procedure is set by the sequence numbers and related on the capacity of facilities according to the constraints [56]. Figure 5(b) shows an example for allocation between the distributors and customers.

3.3. Hybrid optimizers

One of the main contributions of this paper is to utilize four new hybrid optimizers. The last decade has seen a rapid development in the area of nature-inspired metaheuristics resulting in several new algorithms including KA and SFS employed in this study [56][57][58]. The modifications and hybridization of recent metaheuristics have been popular methods too [58][59]. Such hybrid methods aggregate the advantages of different recent and old metaheuristic to improve the exploration and exploitation phases independently or combined [32]. In this work, four new hybrid optimizers based on the advantages of recent and traditional metaheuristics are proposed. In this regard, by using an intelligent design, each recent population-based metaheuristic as the main loop, is hybridized by a local search from the presented traditional single-solution ones. The following sub-sections are presented the four proposed algorithms.

3.3.1. Hybrid of KA & SA (HKASA)

The KA as illustrated by Supplementary Materials F1.3 uses a strong exploitation phase by considering swirling and moving operators [58]. In the term of exploration phase, for each agent of $N3$ group, a set of population is generated randomly [2]. Although the randomization of procedure is good as the nature of metaheuristic, it can be modified by SA structures in per iteration as a sub-loop. Note that SA has been stated clearly in Supplementary Materials F1.1. Accordingly, each Keshtel is compared by the previous one and if it has been improved, it will be replaced. Conversely, SA structure for accepting the rejected solutions is considered by controlling a rate of temperature and its decreasing during the iterations. The proposed HKASA is addressed by the following pseudo-code as given in Figure 6.

3.3.2. Hybrid of SFS & VNS (HFVNS)

In HFVNS, SFS explained by Supplementary Materials F1.4 plays the main actor and the rules of VNS considers as a local search to control the search phases in SFS. The diffusion operator in SFS is modified by a sub-loop from VNS which has been stated by Supplementary Materials F1.2. Instead of Gaussian distribution model, the procedures adopted from VNS are used. It seems that SFS is improved by exploration properties in the developed hybrid algorithm. The pseudo code of HFVNS is given in Figure 7.

3.3.3. Hybrid of KA & VNS (HKVNS)

In the developed HKVNS, we want to keep the exploitation and exploration properties and reduce the time consumption in KA. Instead of three groups of Keshtels, only two of them will

be used. $N1$ includes the set of lucky Keshtels who perform the attracting and swirling process. Also, $N2$ uses the rule of VNS by using the lucky ones. In the initial population, the best solutions are chosen by $N1$ and the rest of them are $N2$. In each iteration, $N2s$ are created by a neighbor from each agent of $N1$ (*i.e.* lucky Keshtels). A VNS sub-loop is considered to do the exploration phase in this case. Figures 8 shows the steps of the HKVNS algorithm.

3.3.4. Hybrid of SFS & SA (HSFSA)

In this hybrid algorithm, the diffusion operator is modified by employing the SA rules. In the term of exploitation phase, a local search is done as per the current temperature. This idea is probed to compare with its general algorithms in different criteria in the experiments. The pseudo-code of HSFSA is given in Figure 9. Generally speaking, the two hybrid algorithms presented for SFS increase the properties of exploration and exploitation phases for HfVNS and HSFSA, respectively. However, the two hybrid optimizers for KA improves the characteristics of exploration faze in two different ways *i.e.* HKASA and HKVNS.

4. Experimental results

In this section, the experimental setup is discussed including initial values for the parameters and generating benchmark problems. Taguchi experimental design method is then utilized to enhance the performance of algorithms. In order to check the metaheuristics, the results in small sizes are validated by an exact approach. In addition, the performances of employed optimizers are assessed by using different criteria. Finally, some sensitivity analyses are proposed to explore the behavior of decision makers in different cases when solving a real dataset. It should be noted that all experiments were done by a Core 2 Duo-2.26 GHz processor laptop. Also, the related codes were written in C++ and built in Microsoft Visual Studio 2014.

4.1. Data generation

To assess the optimizers, a set of benchmark problems with different levels of difficulties is needed [1]. Here, 24 test problems are designed with three difficulty levels (*i.e.* small, medium and large). Table 1 shows the test problems generated for the purpose of this work.

The test problems are generated randomly as given the parameters in Table 2. In addition, the maximum desired number of facility in each decision level is estimated by a half of total number existing for this level.

It should be noted in order to approximate the value of fixed opening cost, storage capacity and safety stocks of facilities, the approach benchmarked from Devika *et al.* [1] has been utilized in our study.

4.2. Taguchi experimental design method

Since the algorithms employed and proposed in this work have several controlling parameter, the best value should be chosen to provide an unbiased comparison [2]. To do this, Taguchi method presented by Genichi Taguchi [61] is employed, in which, signal-to-noise (S/N) ratio indicates the amount of variation in response variable. The higher value brings the better quality of this metric. S/N ratio in the minimizing objective functions should be formulated as follows:

$$S / N = -10 \log_{10} (\text{objective function})^2 \quad (30)$$

The best values for the parameters of the algorithms found by Taguchi method is shown in Table 3.

The test problems are solved 30 times and the following metric (Relative Percentage Deviation) is used to quantify their performance:

$$RPD = \frac{Alg_{sol} - Min_{sol}}{Min_{sol}} \quad (31)$$

where Min_{sol} is the best solution among all solutions and Alg_{sol} is the output of algorithm. The lower value of this metric brings the better quality. Moreover, Taguchi experimental design method proposes an orthogonal array to reduce the number of trials for each algorithm. According to Table 3, Taguchi approach offers L_9 for HFVNS. Also, L_{16} is applied to SFS. For SA and VNS, L_{18} is proposed. In addition, KA uses the orthogonal array of L_{27} . Finally, L_{18} is considered by three other hybrid algorithms: HKASA, HKVNS and HSFSa. Due to page limitation, the results of S/N ratio and mean RPD for each algorithm are reported in Supplementary Materials F2.

As a result, the tuned parameters for each presented metaheuristic are given by Table 4.

4.3. Validation of metaheuristics in small sizes

This sub-section aims to check the quality of developed tri-level metaheuristics with an exact approach for tri-level programming model. A similar method to that in Fathollahi Fard and Hajaghaei-Keshteli [19] is used, in which the first and second levels are solved by an explicit enumeration method and the third level is tackled by an exact solver (*i.e.* GAMS in this study). This means that all levels were solved by exact method. In the proposed methodology, however, all levels are solved by metaheuristics. So, explicit enumeration method is used in this study to compare with metaheuristics. In the explicit enumeration algorithm (EX), all possible nodes should be considered. For instance, there are four potential manufacturers and two of them must be established. Therefore, $\binom{4}{2}$ nodes are existed and must be considered. In the small sizes, this approach is compared by different presented metaheuristics.

Table 5 shows the outputs of the methods. The Gap of best solutions is noticeable in the table. Figure 10(a) depicts the run time for all methods in this case by considering the exact method and tri-level metaheuristics. Besides, Figure 10(b) shows the metaheuristics behavior with each other. Hitting time is defined as the first time that an algorithm finds the best solution. The algorithms are compared by Figure 10(c).

Inspecting the results in Table 5, the quality of solutions for the metaheuristics is the same as the exact approach. The outputs of hybrid optimizers are better or same as recent metaheuristics. The standard deviation for VNS and SA are also more than the other algorithms. By contrast, HKASA shows a lower value. In term of hitting time VNS shows a better convergence rate for small sizes.

4.4. Comparison of hybrid metaheuristics with their individual ones

We run each algorithm 03 times and present the best, worst, average and standard deviation along with the run time and hitting time of employed optimizers in Table 6-7. For medium and

large sizes, the behavior of algorithms in term of solution time and hitting time are depicted by Figure 11 and 12, respectively. As per the results in Figure 11, SA and VNS require less procedure time in all of test problems. Also, HKVNS shows less computational time as compared to hybrid and recent metaheuristics. Conversely, HKASA need a longer time to find a reasonable solution on the majority of test problems. Regarding the rate of hitting time for presented optimizers which can be seen from Figure 12, SA shows a good rate. However, SFS requires a more time to reach the best solution in the term of hitting time.

The behavior of algorithms in three sample problems (*i.e.* P10, P16 and P22) is compared in Figure 13. To have a fair comparison, the stop condition is the maximum number of iteration (200) for all algorithms. As can be seen, HKASA reaches shows the best convergence rate. The worst results are given by SA and VNS.

Finally, in order to verify the statistical validity of results, an analysis of variance (ANOVA) is done to confirm the significance of the results (based on *RPD*). This analysis is conducted for all test problems: small, medium and large sizes have been performed. The results demonstrate that there are substantial differences between the performances of algorithms. Figure 14 illustrates theses validities on the presented metaheuristics. In small-size problems, HKASA shows the best performance among all methods (See: Figure 14(a)). For medium-sizes problems, SFS provides the best performance as seen in Figure 14(b). In the large-size problems, it is evident that KA shows the worst results (See: Figure 14(c)). Meanwhile, there is a little difference between algorithms in large-size problem.

4.5. Sensitivity analyses through a real data set

In the last sub-section, a sensitivity analysis is conducted. A real case study is proposed to set the data of model. Our data set is generated from Mazandaran province in Iran. It is assumed that there are four suppliers, six manufacturers, ten distributors. In addition, 15 zones for demand markets are recognized. These zones are specified by geographical map as seen in Figure 15. Three collectors exist to collect the returned tires and send them to recyclers which are estimated

as two centers. Besides, there are eighteen types of tires for different kinds of cars and trucks in our case study¹.

The best algorithm found in the preceding section i.e. HKASA is used to perform the analysis. The behavior of all three decision levels in a one run is depicted by Figure 16. It is observed that regarding the nature of a tri-level programming model, in major of cases, there are some conflicting points between the decision levels of proposed problem.

As declared by results, the prices of forward and reverse system play a key role in the benefits of each level especially the leader i.e. manufacturers. By considering four different cases numbered as C1 to C4, the prices of recyclers are increased. The range of other parameters is similar to the estimated parameters in sub-section 4.1. Table 8 gives the outputs of the analysis. Figure 17 shows the effects of these changed on the objective function. According to the results, manufacturers choose the lower prices to provide the raw materials. If the prices of recyclers are increased, the manufactures may be purchased the materials from supplier instead of recyclers.

5. Conclusion and future works

In this work, a tri-level decision-making model was proposed to address the tire closed-loop supply chain for the first time. Manufacturers, distributors and collectors were selected as the decision levels and the markets and recyclers and suppliers were the fixed levels. In order to address the developed model, an integrated approach utilizing metaheuristics for all levels, namely, tri-level metaheuristic was applied to tackle the problem. In addition, this paper developed four new hybrid optimizers based on the advantages of two recent metaheuristics i.e. KA and SFS and also two traditional local search-based algorithms i.e. SA and VNS. The validation of used methodology was checked by an exact algorithm. The algorithms were compared quantitatively and qualitatively to choose the best for solving a real case study. It was observed that HKASA was the best optimizer. Finally, a case study was employed to confirm the

¹ <http://www.iran tireco.com/en/employment/default.aspx>

merits of the proposed model. The results can be helpful by giving managerial insights for the tire industry.

Several future works can be recommended. The presented hybrid optimizers can be examined by other large-scale optimization problems. In addition, the results of methods can be compared by other heuristics and metaheuristics. The decision level for tire closed-loop supply chain can be changed by customers and recyclers. Also, the tri-level model may be extended to fourth-level to make the model more realistic. Moreover, some real constraints should be added for future works. For example, considering the vehicle routing operation for each center to develop the mathematical model would be a value continuation as well.

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Figure 1. The scraped tires may be left in nature to pollute the environment (this photo is taken from our case study)

Figure 2. The graphical structure of tire closed-loop supply chain

Figure 3. The structure of tri-level programming model for the closed-loop supply chain

Start

$X(Y_m^M, Y_j^J, Y_n^N, X_{rm}^R, X_{im}^I, X_{mjp}^M, X_{jlp}^J, X_{lnp}^L, X_{nrp}^N)$

(Z_1)

Decision variable of $X(Y_m^M, X_{rm}^R, X_{im}^I)$ is solved

(Z_2)

Decision variable of $X(Y_m^M, Y_j^J, X_{rm}^R, X_{im}^I, X_{mjp}^M, X_{jlp}^J)$ is solved

(Z_3)

NO

Yes

The end

Figure 4. Constructing of the tri-level metaheuristic to solve the proposed tri-level programming model [19]

P_1	P_2	P_3	P_4	P_5
0.34	0.57	0.25	0.68	0.92
$MAX = 3$				
0	1	0	1	1

(a) The graphical illustration of encoding plan for the binary variables (Y_{ij}^0)

(b). An example for the priority-based representation: flow of products and allocation

Figure 5. The proposed encoding plan in two sub-solutions (*i.e.* (a) and (b))

```

Initialize Keshtels population
Calculate the fitness and sort them in three types:  $N_1$ ,  $N_2$  and  $N_3$ 
 $X^*$ =the best solution.
while ( $t$ < maximum number of iteration)
    for each  $N_1$ 
        Calculate the distance between this lucky Keshtel and all Keshtels.
        Select the closest neighbor.
         $S=0$ ;
        while ( $S$ < maximum number of swirling)
            Do the swirling.
            if the fitness of this new position is better than prior
                Update this lucky Keshtel.
                break
            endif
             $S=S+1$ 
        endwhile
    endfor
    for each  $N_2$ 
        Move the Keshtel between the two Keshtels.
    endfor
    for each  $N_3$ 
        Generate a new Keshtel as a new random solution.
        if the function value of the new solution is better than prior
            Replace the new solution as old solution.
        else
            Calculate  $\delta$ ,  $\delta = |f_{old} - f_{new}|$ .
            if  $\text{rand} < \exp(-\delta/T)$ 
                Replace the new solution.
            endif
        endif
    endfor
    Update  $T$ ;
    Merge the  $N_1$ ,  $N_2$  and  $N_3$ 
    Sort the Keshtels and form  $N_1$ ,  $N_2$  and  $N_3$  for next iteration.
    Update the  $X^*$  if there is better solution.
     $t=t+1$ ;
end while
return  $X^*$ 

```

Figure 6. The pseudo-code of HKASA


```

Set the parameters and initialize a population of  $N$  points
A set of neighborhood structures  $N_k$  for  $k=1, 2, \dots, k_{max}$  for shaking.
BP=the best point.
while ( $t <$  maximum number of iteration)
    for each point  $P_i$ 
        /*Do the diffusion process*/
         $k=1$ ;
        while ( $k < k_{max}$ )
            Shaking: pick a random solution  $P_i$  from the  $k^{th}$  neighborhood  $N_k(P_i)$  of  $P_i$ .
             $P_i' = \text{local search}(P_i)$ ;
            if the objectives function of  $P_i'$  is better than  $P_i$ 
                 $P_i = P_i'$ ;
                Continue to search with  $N_i$ ;  $k=1$ ;
            else
                 $k=k+1$ ;
            endif
        endwhile
    endfor
    Do the updating process.
    /*the first updating process*/
    All points are ranked by the following equation:
    
$$Pa_i = \frac{\text{rank}(P_i)}{N}$$

    for each point  $P_i$ 
        if  $\text{rand} > Pa_i$ 
            Updating the position based on the following equation:
            
$$P_i' = P_i - \varepsilon \times (P_i' - P_i)$$

        endif
    endfor
    /*the second updating process*/
    All points are ranked by the following equation:
    
$$Pa_i = \frac{\text{rank}(P_i)}{N}$$

    for each point  $P_i$ 
        if  $\text{rand} > Pa_i$ 
            Updating the position based on the following equations:
            
$$P_i'' = P_i' - \varepsilon \times (P_i' - BP), \text{ if } \varepsilon' \leq 0.5$$

            
$$P_i'' = P_i' - \varepsilon \times (P_i' - P_r'), \text{ if } \varepsilon' > 0.5$$

        endif
    endfor
    Update the PB if there is better point.
     $t=t+1$ ;
end while
return BP

```

Figure 7. The pseudo-code of HFVNS

```

Initialize Keshtels population
Calculate the fitness and sort them in three types:  $N_1$  and  $N_2$ .
A set of neighborhood structures  $N_k$  for  $k=1, 2, \dots, k_{max}$  for shaking.
 $X^*$ =the best solution.
while ( $t <$  maximum number of iteration)
    for each  $N_1(LK)$ 
        Calculate the distance between this lucky Keshtel and all Keshtels.
        Select the closest neighbor.
         $S=0$ ;
        while ( $S <$  maximum number of swirling)
            Do the swirling.
            if the fitness of this new position is better than prior
                Update this lucky Keshtel.
                break
            endif
             $S=S+1$ 
        endwhile
    endfor
    for each  $N_2$ 
         $k=1$ ;
        while ( $k < k_{max}$ )
            Shaking: pick a random solution  $N_2$  from the  $k^{th}$  neighborhood  $N_k(LK)$  of  $N_2$ .
             $N_2'$ =local search ( $LK$ );
            if the objectives function of  $N_2'$  is better than  $N_2$ 
                 $P_i = P_i'$ ;
                Continue to search with  $N_1$ ;  $k=1$ ;
            else
                 $k=k+1$ ;
            endif
        endwhile
    endfor
    Merge the  $N_1$  and  $N_2$ 
    Sort the Keshtels and form  $N_1$  and  $N_2$  for next iteration.
    Update the  $X^*$  if there is better solution.
     $t=t+1$ ;
end while
return  $X^*$ 

```

Figure 8. The pseudo-code of HKVNS

Set the parameters and initialize a population of N points.
BP=the best point.

while ($t < \text{maximum number of iteration}$)

for each point P_i

 /*Do the diffusion process*/

$P_i' = \text{Create a neighbor for } P_i$

if the function value of the P_i' is better than P_i

$P_i = P_i'$;

else

 Calculate δ , $\delta = |f_{old} - f_{new}|$.

if $\text{rand} < \exp(-\delta/T)$

 Replace the new solution.

endif

endif

endfor

 Do the updating process.

 /the first updating process/

 All points are ranked by the following equation:

$$Pa_i = \frac{\text{rank}(P_i)}{N}$$

for each point P_i

if $\text{rand} > Pa_i$

 Updating the position based on the following equation:

$$P_i' = P_i - \varepsilon \times (P_i' - P_i)$$

endif

endfor

 /the second updating process/

 All points are ranked by the following equation:

$$Pa_i = \frac{\text{rank}(P_i)}{N}$$

for each point P_i

if $\text{rand} > Pa_i$

 Updating the position based on the following equations:

$$P_i'' = P_i' - \varepsilon \times (P_i' - BP), |\varepsilon| \leq 0.5$$

$$P_i'' = P_i' - \varepsilon \times (P_i' - P_r'), |\varepsilon| > 0.5$$

endif

endfor

 Update T ;

 Update the PB if there is better point.

$t = t + 1$;

end while

return BP

Figure 9. The pseudo-code of HSFSA

(a)

(b)

(c)

Figure 10. The behavior of methods in term of CPU and HT for small sizes (*i.e.* (a) for CPU by considering the exact method, (b) CPU without the exact method and (c) for HT for metaheuristics)

(a)

(b)

Figure 11. The behavior of methods in term of solution time (*i.e.* (a) for medium sizes and (b) for large sizes)

(b) **Figure 12.** The behavior of methods in term of hitting time (*i.e.* (a) for medium sizes and (b) for large sizes)

(a)

(b)

(c)

Figure 13. The behavior of metaheuristics in a same iteration (*i.e.* (a) for P10, (b) for P16 and (c) for P22)

(a)

(b)

(c)

Figure 14. Means plot and LSD intervals for the presented algorithms (*i.e.* (a) for small sizes, (b) for medium sizes and (c) for large sizes)

Figure 15. The customer zones in our case study from Mazandaran province [15]

Figure 16. The behavior of decision levels from one run for our case study

Figure 17. The behavior of objective function

Table 1. The level, number and size of test problems

The levels of problem	Number of problem (P_i)	Size of problems (I, M, J, L, N, R, P)
Small	P1	(7, 5, 10, 9, 4, 3, 10)
	P2	(11, 8, 12, 13, 5, 4, 10)
	P3	(14, 12, 16, 15, 8, 7, 10)
	P4	(17, 16, 15, 16, 11, 10, 10)
	P5	(19, 14, 17, 19, 14, 12, 10)
	P6	(23, 16, 21, 20, 15, 13, 10)
	P7	(25, 29, 30, 31, 19, 18, 10)
	P8	(27, 30, 32, 32, 21, 19, 10)
Medium	P9	(34, 32, 33, 35, 23, 20, 10)
	P10	(37, 35, 34, 37, 25, 21, 10)
	P11	(41, 37, 36, 39, 27, 22, 10)
	P12	(43, 39, 38, 41, 29, 23, 10)
	P13	(45, 43, 36, 39, 27, 23, 10)
	P14	(47, 46, 38, 41, 29, 24, 10)
	P15	(49, 49, 40, 44, 32, 26, 10)
	P16	(52, 44, 42, 46, 32, 26, 10)
Large	P17	(67, 55, 59, 111, 36, 31, 10)
	P18	(71, 57, 61, 115, 37, 32, 10)
	P19	(75, 59, 63, 119, 39, 33, 10)
	P20	(79, 61, 65, 123, 40, 34, 10)
	P21	(83, 63, 67, 127, 42, 35, 10)
	P22	(87, 65, 69, 131, 43, 36, 10)
	P23	(90, 69, 73, 136, 46, 38, 10)
	P24	(94, 72, 76, 140, 49, 40, 10)

Table 2. Parameters and their surfaces

Parameters	Surfaces
PC_i^I	$rand\{3, 4\}$
PC_r^R	$rand\{1, 2\}$
$PC_{mp}^M, PC_{jp}^J, PC_{np}^N, PC_{lp}^L$	$rand\{5, 6, \dots, 10\}$
$MC_{mp}^M, MC_{jp}^J, MC_{np}^N$	$rand\{3, 4, \dots, 8\}$
$TC_{\square}^{\square}$	$rand\{3, 4, \dots, 10\}$
H_{mp}^M, H_{jp}^J	$rand\{4, 5, \dots, 8\}$
H_{np}^N	$rand\{2, 3, \dots, 5\}$
d_{lp}	$\sim N(20, 4)$
a_{lp}	$\sim N(0.2, 0.6)$

Table 3. The list of algorithm's parameters and their levels

Algorithms	Parameters		Levels			
	Notation	Description	1	2	3	4
KA	MaxIt	The maximum number of iteration	200	300	500	-
	nPop	The number of initial population	100	150	200	-
	PN1	The percentage of $N1$ Keshtels	0.2	0.3	0.4	-
	PN2	The percentage of $N2$ Keshtels	0.1	0.2	0.3	-
	Smax	The maximum number of swirling	2	3	4	-
SFS	MaxIt	The maximum number of iteration	150	200	250	300
	nPop	The number of initial population	100	150	200	250
	MDN	The maximum number of diffusion process	1	2	3	4
SA	MaxIt	The maximum number of iteration	300	500	700	-
	SubIt	The maximum number of sub-iteration for sub-loop	20	30	50	-
	T0	Initial temperature	1000	1500	2000	-
	Tdamp	The rate of reduction temperature	0.9	0.99	-	-
	Mn	The procedure of neighboring	Swap	Reversion	Insertion	-
VNS	MaxIt	The maximum number of iteration	500	800	-	-
	K	Number of neighbors shake	1 (<i>i.e.</i> Swap)	2 (<i>i.e.</i> Swap and Reversion)	3 (<i>i.e.</i> Swap, Reversion and Insertion)	-
HKASA	MaxIt	The maximum number of iteration	200	300	500	-
	nPop	The number of initial population	100	150	200	-
	PN1	The percentage of $N1$ Keshtels	0.2	0.3	0.4	-
	PN2	The percentage of $N2$ Keshtels	0.1	0.2	0.3	-
	Smax	The maximum number of	2	3	4	-

		swirling				
	T0	Initial temperature	1000	1500	2000	-
	Tdamp	The rate of reduction temperature	0.9	0.99	-	-
HFVNS	MaxIt	The maximum number of iteration	200	300	500	-
	nPop	The number of initial population	100	150	200	-
	K	Number of neighbors shake	1	2	3	-
HKVNS	MaxIt	The maximum number of iteration	300	500	-	-
	nPop	The number of initial population	100	150	200	-
	PN1	The percentage of N1 Keshtels	0.2	0.3	0.4	-
	Smax	The maximum number of swirling	2	3	4	-
	K	Number of neighbors shake	1	2	3	-
HSFSA	MaxIt	The maximum number of iteration	200	300	500	-
	nPop	The number of initial population	100	150	200	-
	T0	Initial temperature	1000	1500	2000	-
	Tdamp	The rate of reduction temperature	0.9	0.99	-	-
	Mn	The procedure of neighboring	Swap	Reversion	Insertion	-

Table 4. The tuned parameters of algorithms

Algorithms	Parameters
KA	MaxIt=500; nPop=200; PN1=0.2; PN2=0.2; Smax=3;
SFS	MaxIt=250; nPop=250; MND=4;
VNS	MaxIt=800; K=3;
SA	MaxIt=700; SubIt=30; T0=2000; Tdamp=0.99; Mn=Reversion;
HKASA	MaxIt=500; nPop=200; PN1=0.4; PN2=0.3; Smax=3; T0=1500; Tdamp=0.99;
HFVNS	MaxIt=500; nPop=200; K=3;
HKVNS	MaxIt=500; nPop=200; PN1=0.3; Smax=4; K=1;
HSFSA	MaxIt=500; nPop=150; T0=1000; Tdamp=0.99; Mn=Insertion;

Table 5. The results of algorithm in small sizes ($Gap = \frac{Z_{SOL} - Z_{EX}}{Z_{EX}}$, CPU=consuming time, OUT=output of method: the value of the first level objective function; SD=standard deviation; HT=hitting time)

Algorithms		P1	P2	P3	P4	P5	P6	P7	P8
EX	OUT	634	38244	1786452	5178906	5869463	6755842	28331655	36482531
	CPU	344	5710	151838	199466	314212	500481	900208	1167884
KA	OUT	634	40673	1943765	5466345	6794232	7054774	29937066	37865514
	CPU	478	624	1167	1245	1536	1672	2209	3454
	HT	183	385	671	962	1078	1174	1598	2833
	SD	0	0	18245.15	89457.8	158422	114726.7	568422	792164
	Gap	0	0.000006	0.088	0.0555	0.15755	0.04424	0.05666	0.03790
SFS	OUT	634	40673	1964738	5478251	6944536	7068346	30157462	38316547
	CPU	588	661	1354	1467	1726	1933	2467	3987
	HT	394	513	1065	1189	1425	1367	1825	2032
	SD	0	0	21476.92	94185.1	170647	121447.6	682576	658934
	Gap	0	0.000006	0.0997	0.0578	0.1831	0.0462	0.0644	0.05027
SA	OUT	634	40673	1985322	5567329	7355678	7158953	33648752	38578475
	CPU	486	521	1041	1135	1491	1582	2145	3014
	HT	218	362	653	715	1065	1264	1873	2166
	SD	0	792.97	27183.53	106745.3	213687	123859.3	822143	813562
	Gap	0	0.000006	0.1113	0.0750	0.2532	0.0596	0.18767	0.05745
VNS	OUT	634	40673	1964351	5538914	6955232	7144398	32893651	38169542
	CPU	435	563	978	1092	1323	1410	1915	2968
	HT	219	438	512	854	715	821	1327	2491
	SD	0	842.55	19867.43	97435.2	215756.2	112633.7	748521	977834
	Gap	0	0.000006	0.0995	0.0695	0.1849	0.05751	0.16102	0.04624
HKASA	OUT	634	39822	1883702	5438925	6432913	6852742	30648220	38647158
	CPU	514	695	1206	1398	1753	2371	2541	4012
	HT	187	431	725	892	1327	1954	1926	2841
	SD	0	538.28	16542.85	76345.2	165473	106554.7	437819	674821
	Gap	0	0.000004	0.0544	0.0502	0.0959	0.01434	0.0817	0.05933
HFVNS	OUT	634	40673	1932766	5647232	6748932	7066543	29145692	38557169
	CPU	612	645	1287	1389	1673	2185	2317	3503
	HT	348	517	736	819	1053	1582	1825	2361
	SD	0	0	18542.38	84291.5	159547	119856.3	619054	684923
	Gap	0	0	0.0819	0.0904	0.1498	0.04598	0.02873	0.05686
HKVNS	OUT	634	40673	1925804	5366910	6533184	7183295	29668523	38973615
	CPU	504	536	1187	1272	1416	1978	2467	3683
	HT	407	475	874	1156	1285	1543	2185	2763
	SD	0	729.31	25317.89	96438.1	186477	126558.4	522614	538511
	Gap	0	0.000006	0.0780	0.03630	0.11308	0.06327	0.04718	0.06828
HSFSA	OUT	634	40673	1983314	5428129	6658316	7216554	29872436	38591173
	CPU	518	548	1275	1465	1617	2034	2573	3874
	HT	321	363	897	1043	1285	1753	2174	2896
	SD	0	0	21635.82	102572.3	174393	119949.1	589156	562897
	Gap	0	0.000006	0.1101	0.0481	0.1343	0.0681	0.05438	0.05779

Table 6. The results of algorithms in medium sizes (B=best, W=worst, M=mean).

Algorithms		P9	P10	P11	P12	P13	P14	P15	P16
KA	B	47368194	56379218	71560375	86794355	78660852	95490322	115750493	130508422
	W	49378215	60229514	73280513	87942506	81550824	98340218	121618765	132509318
	M	48142306	57852939	72192465	87070409	79424280	96215857	117940134	131134144
	SD	858935.3	1621788	672669.4	388419.3	976841.2	1095466	2234100	747366
	CPU	2854	4167	5188	5573	7367	8254	8913	9435
	HT	1933	3451	3719	3166	5097	6518	6732	7180
SFS	B	47590134	57228415	70842275	87052788	79578622	95731804	116854903	131043626
	W	50178433	60189455	72843902	88100436	80762294	98478322	122207685	133021788
	M	48640002	58461998	71772803	87486113	80074134	96657361	118492111	131736927
	SD	873232.7	901495.5	713596.9	373102	489590.3	1062298	1848624	728826.23
	CPU	3214	4586	5186	5893	7519	8322	9150	9734
	HT	1895	3893	4275	4285	6053	6218	7502	8187
SA	B	48726155	58402518	70582904	87390214	79632508	96570352	116743512	131390527
	W	50614892	61304276	72168846	88570425	81550934	98567430	122478303	134025783
	M	49641341	59805057	71376880	87863302	80605331	97358185	119362223	132592496
	SD	707933.03	1045779.2	510833	427702.7	755394.7	792318.7	1999902	922030.1
	CPU	2567	3185	4507	5109	5722	6488	7913	8452
	HT	1627	2852	3182	4278	3186	5265	6054	7278
VNS	B	48270125	59350216	70038172	87043722	80550628	96053813	116589413	131390428
	W	51490266	61447328	72548942	88754013	82753406	98475518	122358725	135108549
	M	49473396	60296901	71179714	87833574	81565248	96975120	118809951	133153442
	SD	1056406	732496.4	863434.54	560975.4	1038149	888058	2302676	1321931.4
	CPU	2426	3379	4334	4897	6276	6921	8254	8543
	HT	1865	2519	2953	3865	5732	5367	6243	7158
HKASA	B	47863721	56331852	69483326	86590423	78642506	95137589	115026734	129632860
	W	49032564	59448215	72842248	87590484	81095632	97861352	121675532	133201784
	M	48150967	57799686	70466975	86829144	79346786	95824804	115913240	130553624
	SD	386221.2	1189708.8	1293214.3	358938	1052124	1085812	2298794	1262423.1
	CPU	3058	4367	5392	5813	7516	8461	9158	9671
	HT	2275	3681	3913	4103	4613	5921	5825	6135
HFVNS	B	47489322	57115268	70158634	87032517	78849056	96314508	116032584	130285902
	W	50226317	59842612	72660822	87990534	80972431	98678503	122301982	134724816
	M	48405293	58172007	71006254	87409059	79588606	97256686	118455486	130581830
	SD	1028300.4	1020797.1	1082268	375213.9	746725	911431.3	2330497.1	1126188.5
	CPU	2820	3982	4760	5395	6897	7621	8702	9138
	HT	1765	2319	2942	3816	4275	6174	7217	8259
HKVNS	B	47829133	57139204	70526608	86890435	78905422	96140329	115490326	130195672
	W	50367288	60278845	73048625	88570423	80558794	98674210	122843702	133569436
	M	48837783	58342723	71656097	87421956	79457267	97365555	117795425	131448493
	SD	1091983	1201047	838710	655169.3	684407.9	970813	2905090.6	1426765.3
	CPU	2640	3773	4761	5235	6821.5	7587.5	8583.5	8989
	HT	1654	2418	2914	3627	5031	5389	5924	7143
HSFSA	B	48631255	57042566	70526642	86559302	79536728	96150438	116480322	130926675
	W	50279132	61594285	72446708	87460366	81042604	98879430	121468304	134226804
	M	49171366	59191277	71076788	86938075	80136360	97386938	118593911	132076960
	SD	694189.1	1764377	749320.9	357762.3	565234.7	1052370	1840957.7	1233427.6
	CPU	2890	3885	4846	5501	6620	7405	8531	9093
	HT	1763	2910	3473	4037	4852	5281	6764	6419

Table 7. The results of algorithms in large sizes.

Algorithms		P17	P18	P19	P20	P21	P22	P23	P24
KA	B	453892142	535894024	619736844	654823889	682480972	825687902	931859302	1018953622
	W	464950340	556702542	621746204	673920135	692159425	840313293	964499223	1135435470
	M	457735206	541201591	620555159	660000459	684563377	829558417	943765304	1053949835
	SD	4194385	8373931	738196.4	7641154.16	3276387.3	5852345.5	13183943.5	41711061.1
	CPU	12832	13647	14843	15726	17218	18374	19681	20164
	HT	8903	9714	10251	10897	13428	13892	15425	16829
SFS	B	461095832	538871290	619593204	655270188	681780444	826785992	941859642	1085490322
	W	467328102	553491204	621835266	663809145	698745223	841465486	965594376	1185370268
	M	463336236	544429155	620652030	658792692	688825291	831358449	949440137	1128661610
	SD	2298599.7	5704208.5	784172.6	3452651.93	6312213.35	5535731.13	7057310.18	37970564.4
	CPU	13574	14243	16375	17205	18154	19632	21054	22417
	HT	9743	10326	10843	10725	11439	12754	12923	14062
SA	B	462504631	542042566	620167842	652901675	685326798	827516820	943026842	1096585240
	W	470148253	560327114	622186437	673902194	697325418	849210456	962759042	1150932744
	M	466089111	549982210	621018007	663077770	690788869	838864723	950932829	1123673887
	SD	2529774.6	6148538.6	772273.84	6528897	3804185.66	7258949.57	6103689.29	19169868.8
	CPU	10732	11854	12106	12548	13287	14065	14622	15392
	HT	7435	9215	10632	11433	9784	10822	11437	11829
VNS	B	461794832	540867542	619832487	653189530	684269825	826439024	943872164	1082473912
	W	469382174	558319306	621874953	668429315	697452810	846527910	970328492	1162385904
	M	465210359	549103295	620740654	660377064	684709258	835330990	955941856	1122349483
	SD	2687790	6505083.8	767769.206	4914794.78	2406872.75	6833056.8	8713729.53	26787737.5
	CPU	10365	10854	11437	12679	12935	13209	14825	15632
	HT	7934	9452	10268	11539	12036	12847	13092	13627
HKASA	B	453672186	532564372	619206145	647390216	678324678	821054362	931705462	1022634788
	W	468726170	551674386	621186432	661458795	682214582	839437184	953820912	1118423906
	M	457078470	538372040	619794448	650064553	679164679	826199891	936446709	1042585566
	SD	5051986.3	6759865.9	700824.823	4478698.74	1282530.5	7530075.4	7433018.33	34108027.9
	CPU	13627	14296	15621	16328	18513	20173	22537	24072
	HT	8977	10534	11762	11351	13275	12809	14185	15311
HFVNS	B	460864238	541906543	619428614	648239015	682453167	825648932	935136742	1031278430
	W	467204652	558214350	621426082	662451955	698854236	837218455	954678193	1137823091
	M	461286932	547561265	619916723	652507392	688681808	829430003	942658941	1065791640
	SD	1608614.5	5857257.9	681089.65	5622396.23	5720400.13	4178682	6871135.99	38335259.2
	CPU	12290	12887	14399	15394	16066	17062	18562	19703
	HT	10483	11928	12702	12835	13849	12532	13674	15263
HKVNS	B	451209552	540427482	620642188	650325167	684536226	827750941	932768492	1025643819
	W	470251869	560319472	621972416	666843628	697426044	842206462	953682172	1162478390
	M	459875183	547595993	621221304	655177948	687501947	833110661	941317345	1066990964
	SD	7162596.6	7736031.6	486577.81	5492779.14	4514986.52	5521878	7698611.13	43246864.9
	CPU	11351	11971	12799	13897	14648	15275	16767	17444
	HT	8533	9521	10186	10794	11295	12378	13026	14276
HSFSA	B	458765489	537248391	619527046	651489322	682241560	826437024	934803286	1012436285
	W	469743261	553802164	621488362	669432784	697342562	842561046	953872902	1128634166
	M	462643992	544150653	620311861	655354379	687427904	832287260	941362289	1050184802
	SD	3771856.2	6353398.4	732277.567	5781200.36	5314422.55	5898405.41	6724905.94	40095779.6
	CPU	11746	13286	14563	15295	15821	16795	17349	19386
	HT	8725	9511	12437	8765	14676	13253	14206	16811

Table 8. The sensitivity analyses on the price of raw materials

Number of cases	(PC_i, PC_r)	Objective function (Z_1)
C1	(4, 1)	98938525
C2	(4, 2)	101043946
C3	(4, 3)	102378254
C4	(4, 4)	105380241