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Sustainable tire closed-loop supply chain network design: Hybrid metaheuristic algorithms for large-scale networks

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ABSTRACT

Growing environmental concerns and social legislations enforce decision makers to design their supply chains considering environmental and social impacts as well as economical objectives. Degradation difficulties and recovering profits lead to recycle scraped tires regarding the sustainability factors. This paper firstly develops a multi-objective mixed integer linear programming model for designing of sustainable tire closed-loop supply chain network. The proposed model aims to optimize total cost, environmental impacts of establishment of facilities, processing of tires and transportation between each level as well as social impacts including job opportunities and work's damages. To alleviate the drawbacks of existing metaheuristic algorithms when solving the large-scale networks, four new hybrid metaheuristic algorithms based on the advantages of recent and old ones are developed. To evaluate the quality of the proposed hybrid algorithms, extensive computational experiments, comparison, and sensitivity analyses are conducted with different criteria. Results reveal that hybrid algorithms are effective approaches to solve the underlying problem in large-scale networks.

1. Introduction

According to the U.S. Environmental Protection Agency (EPA) report, world demand for tires is increasing 4.1 percent per year and reaches to 3.0 billion units in 2019 (Amin et al., 2017). Hence, economic design of tire supply chain network became an important issue for both academics and practitioners (Stadtler, 2015). In addition, EPA reported that about 290 million scraped tires are disposed every year. Unfortunately, the amount of the scraped tires that are released in the nature without environmental consideration threaten human health, water, air, and soil condition (Subulan et al., 2015a). Concerns aroused when twenty percent of scarped tires are illegally dumped in landfills or roadsides. To tackle these issues, supply chain managers need to develop sustainable network for managing tire supply chain considering economic, social, and environmental factors (Pishvaee et al., 2014). Whereas, in the literature less attentions has been paid for designing sustainable tire closed-loop supply chain network (Govindan et al., 2016).

Todays, growth of recycling technologies and environmental regulations led to convert recyclable items into raw material that can be used in new products (Amin et al., 2017). Dehghanian and Mansour (2009) designed recovery network to mitigate the negative environmental and social impact of the end-of-life products such as tire. They used Life-Cycle Assessment (LCA) based methodology for estimating social and environmental impacts and indicated different measures for each stage. Identifying the social and environment measures, the stages of the product's life cycle, and estimating the overall impact of products were presented as main challenges of the LCA-based methodology (Dehghanian and Mansour, 2009). While the authors aim to integrate the forward and reverse flows of supply chains to improve the performance of the networks, Dehghanian and Mansour (2009) considers forward flow between collection centers and recycling plants. Therefore authors aims to develop sustainable supply chains by considering forward and revers flows. For example, Diabat et al. (2015) considered remanufacturing centers in supply chain that were collecting recyclable items, remanufacturing them, and then distribute them among retailer. Kaya and Urek (2016) designed closed-loop supply chain network considering both distribution and collection decisions. To increase the total profit of supply chain network, they determined incentive values for collecting right amount of recyclable items. Özceylan et al. (2016) designed closed-loop supply chain network for recycling end-of-life vehicles under

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regulation by Republic of Turkey Ministry of Environment and Urbanization. Zhalechian et al. (2016) presented sustainable closed-loop supply chain model by considering CO_2 emissions, fuel and energy consumption, and the social impacts of new job opportunities. Recently, Soleimani et al. (2017) proposed three kinds of recycling *i.e*. product, components, and raw material by accounting environmental impact, total profit of network, and lost working. Opening or closing of network's node and product flow among them were determined by concerning responsiveness to customer demand as well as sustainability factors. Among studies have modeled the closed-loop supply chain problems; there still exists a gap in the modeling of economic, environmental and social dimensions concurrently (Samadi et al., 2018).

To cope with the described problem, this study designed sustainable tire closed-loop supply chain network considering the economic, environmental and social dimensions. Different measures for each stage of manufacturing, recycling, and transportation along supply chain has been presented to estimate the social and environmental impact of tire in closed-loop supply chain. Four new hybrid multi-objective metaheuristic algorithms were developed to encounter with the complexity of the large scale networks. The proposed algorithms are tested with different random generated test problems. In addition, to generalize the proposed algorithms, ten standard benchmarked functions were solved and results are compared with well-known multi-objective algorithms. The main contributions of this paper can be outlined as follows:

- Developing a new model of the sustainable tire closed-loop supply chain network for the first time;
- Proposing four new hybrid meta-heuristic algorithms to reduce the computational time and improve the quality of solutions;
- Generalizing the performance of the proposed hybrid meta-heuristic algorithms using standard benchmarked problems;
- Developing the LCA-methodology for estimating the sustainability dimensions of the tire closed-loop supply chain network.

The rest of the paper is organized as follows. The relevant literature is reviewed in Section 2. The proposed model of tire sustainable closed-loop supply chain network is formulated in Section 3. Section 4 presents the hybrid meta-heuristic algorithms along with brief review of basic algorithms. Computational experiments, comparison, and sensitivity analyses are reported in section 5. Finally, Section 6 provides concluding remarks and directions for further research.

2. Literature review

Generally, supply chain management aims to find the best strategies for controlling and managing the supply chains. One of the well-known problems in supply chain management is Supply Chain Network Design (SCND) (Eskandarpour et al., 2017). Scholars solve SCND problems for improving the products flow between different levels such as suppliers, manufacturers, retailers, and customers (Badri et al., 2013). Several researches in the relevant literature have focused on SCND problems considering different features of real cases such as products' characteristics (Coelho and Laporte, 2014), number of levels (Srivathsan and Kamath, 2017), network flows (Ivanov et al., 2017), transportation (Cui et al., 2016), effects of different types of technologies (Fard et al., 2017), specifications of supplier, manufacturer, and distributer facilities (Shafiee et al., 2014). Indeed, the SCND problems become more complicated considering more features of real cases. To design tire supply chain network different features should be considered including *i*) tires are recyclable item and should be recycled and remanufactured; *ii*) a network should be designed with four levels consisting of raw material suppliers, manufacturer/recycler, retailer/collection center, customer; *iii*) forward flows start from supplier and end to customer and reverse flow from collection center to manufacturer or supplier. Taken together, the scholars have developed the closed-loop supply chain for designing network of recyclable items along with considering the sustainable dimensions (Paydar et al., 2017).

2.1. Closed-loop supply chain

Regarding the recent recycling and remanufacturing technologies developed, the researchers have paid more attentions to integrate forward and reverse logistics as closed-loop supply chain network (Xie et al., 2017). Among them, Özceylan et al. (2016) emphasized that environmental and social concerns and legislations motivate the decision makers for designing closed-loop supply chains. A linear programming model has been developed to distribute new vehicles and collect end-of-life vehicles from customers. However their model was not considered the facility locations decisions and multiple suppliers. In addition, they suggested that heuristics approaches should be developed to cope with large scale networks. Mohammed et al. (2017) optimized industry environmental impact and total cost for designing and planning a multi-period, multi-product closed-loop supply chain network. Their model evaluated the trade-offs between carbon emissions as industry environmental impact and total cost. Although their multi-stage scenario-based stochastic approaches could provide robust solutions, for solving real cases (*i.e*. large-scale networks) desirable approaches should be developed (Mohammed et al., 2017). Paydar et al. (2017) presented a bi-objective optimization model for closed-loop supply chain of used engine oil. Their model maximizing profit and minimizing risk of closed-loop supply chain under different scenarios. Increasing the size of problems, their solution approach is encountering with computational cost. Most of scholars confirmed that the complexity of underling problem would be increased significantly to deal with large scale networks (Fahimnia et al., 2015). This reason motivated several researchers like this study to contribute the new capable meta-heuristic algorithms for solving such problems.

2.2. Sustainable supply chain network design

Another issue which should be considered for developing closed-loop supply chain network is to consider the sustainability dimensions. Regarding the real applications of this issue, recent studies considered different types of objective functions to develop the sustainable supply chain network design (Soleimani et al., 2013). Note that most of researches focus on economic objective function such as profit or cost. Although more attentions have been paid on the environmental impact of supply chain recently, limit researches were considered the social impact of closed-loop supply chain yet. Scholars should be aimed to integrate the environmental impacts of supply chains' operations as well as the health and safety of employees and society (Zhalechian et al., 2016). Sustainability theory leads decision makers to integrate economic, environmental, and social dimensions for designing closed-loop supply chain network (Boukherroub et al., 2015; Genovese et al., 2017). Mota et al. (2015) developed a multi-objective mathematical programming model for planning closed-loop supply chain. LCA as a reliable method for evaluating environmental impact (introduced by European CommissionE, 2010), negative impact of unemployed people in society, and total cost of network were considered for designing network. They are emphasized that social factors should be improved for evaluating social dimension of supply chain.

Soleimani et al. (2017) proposed a multi-objective mathematical model aim to optimize CO_2 emissions, profit of the chain, and the number of missed working days. They highlighted that more attempt need for quantifying the social and environmental impact as well as meta-heuristic algorithms to solve large-scale networks. Nevertheless few studies have been developed quantitative approaches for adopting the whole dimensions of the sustainability in the closed-loop supply chain. Recently, Ansari and Kant (2017) explored the main knowledge gaps and research opportunities of sustainable supply chain management. Quantifying the social and environmental dimensions of the sustainability, implementing sustainability in real complex cases such as automobile industries, and multi-objective meta-heuristic algorithms were introduced as main gaps in the sustainable closed-loop supply chain literature (Ansari and Kant, 2017).

Designing sustainable closed-loop supply chain networks would be lead to *i*) reducing the harmful impact of tires on environment, *ii*) increasing profits of network, and iii) improving the social impact through recycling and remanufacturing process (Mani et al., 2015). Hence, Among different relevant product to automobile industry, tire is the one of the most important products (Kannan et al., 2014; Subulan et al., 2015a). However, most attentions have been paid on economic dimension of closed-loop tire supply chain. For example, Amin et al. (2017) optimized closed-loop supply chain based on the tire remanufacturing options. Their model analyzed a real case study in Canada by calculating just net present value of the problem. Pedram et al. (2017) studied the application of tire closed-loop supply chain for maximizing profit and managing waste. They determined location of the facility and material flows through formulating a mixed integer linear programming model. To the best of our knowledge, scholars have not been carried out adoption of sustainability in the supply chain of the tire industry yet.

2.3. Sustainable closed-loop supply chain network design

Generally speaking, the sustainable closed-loop supply chain can be formulated and modeled with different elements. Although adding more factors makes this problem more practical, this increases the difficulty and computational costs for solving of this problem when facing the real world cases (Eskandarpour et al., 2015). That's why this research focuses on the types of mathematical models along with capable solution approaches regarding the computational complexity of this problem in real applications.

Here, a comprehensive review collected by searching in Scopus (between January-2015 to May-2017) is presented. The main keywords to find articles are including sustainability, closed-loop supply chain, and supply chain network design. Since this research focuses on the applicability of the operation and computational research, we search in international journals that have the highest relevant contributions to our study such as Journal of Cleaner Production, Computer & Operations Research, European Journal of Operations Research, Computers & Industrial Engineering, International Journal of Production Economics, Omega, and also Journal of Operations Management. Table 1 summarizes a brief review of relevant studies in literature.

Regarding Table 1, a number of literature gaps according to the recent review papers can be addressed as follows. First of all, studies show that most of developed supply chain networks were proposed in a general topic (Soleimani et al., 2016). Accordingly, considering the applications of SCND by a special type of product *e.g.* tire, battery and food is still scarce. (Govindan et al., 2015a,b). As noted by Soleimani and Govindan (2014), scholars did not pay attention to the types of technologies for manufacturing and recycling (affecting on quality and cost) yet. Furthermore, the most important decisions in such decision-making models are to consider the best optimal locations for facilities and allocation between different levels (Govindan et al., 2016; Govindan and Soleimani, 2017). Note that these decisions are common between the most of mentioned papers as seen in Table 1.

Another main similarity is that most of researchers developed mixed integer linear programming model for designing closed-loop supply chain network (Govindan et al., 2016; Govindan and Soleimani, 2017). According to the sustainability dimensions, the researchers focused mostly on economic and environmental dimensions (Kumar et al., 2014). To the best of our knowledge, only six researchers including Kannegiesser et al. (2015), Zhalechian et al. (2016), Tahirov et al. (2016), Soleimani et al. (2017) and Sgarbossa, and Russo (2017) and also Arampantzi and Minis (2017) considered economic, environmental, and social dimensions, simultaneously. Accordingly, there is no study to propose a sustainable closed-loop supply chain network design for the application of tire industry. In this study, authors aim to response to all mentioned gaps for the literature review. Another contribution of this study is based on the computational research perspective. According to the literature review, most of the studies were encountered with the NP-*hard* problem (Govindan et al., 2015a,b). Hence, solving the large scale networks by heuristics and or metaheuristic algorithms is imperative (Wang et al., 2016). Regarding this issue, this study not only uses old and recent metaheuristics but also four new hybrid ones are introduced to tackle the developed NP-*hard* problem.

3. Problem modeling

This paper considers the multi-level tire closed-loop supply chain including supplier, manufacturer, distributer, customer, collectors, and recyclers. Manufacturer supplies the raw material of the tires from supplier. Then, manufactured tires are distributed in market by distributers. Collectors collect a part of the scraped tires that were used by customers in markets and send to recycler facilities. After recycling, the recycled material can be back to tire supply chain for manufacturing tires or sent to other industries as raw material. The 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 has been shown in Fig. 1 schematically.

This study aims to model the supplier selection and location-allocation problems for designing sustainable tire closed-loop supply chain network. The problem is considered as a multi-level, multi-product network with multiple nodes among levels as shown in Fig. 1. Each facility of supply chain can be opened in each potential location with specific opening fixed cost ($FC_{\square}^{\square}$), variable cost ($VC_{\square}^{\square}$), maximum number of each facility in per level ($MAX^{\square}$), and capacity ($CAP_{\square}^{\square}$) and also transportation cost between other facilities ($TC_{\square}^{\square}$). For example, fixed and variable cost for opening manufacturing plant in the potential location m with capacity CAP_{mp}^{MP} (for product p) is considered with FC_{mt}^{M} and VC_{mt}^{M} by considering manufacturing technology type t. In addition, transportation costs have been considered for transporting tires and raw materials between levels. Transportation cost of product p between manufacturer plant m and distributer center j is TC_{mjp}^{MJ}. Manufacturer (m) can supply the raw material from supplier (i) or recycler (r) with different price PC_i^I or PC_r^R. In addition, for manufacturing tire type p, different type of technology t is existed with the rate of B_{pt} for the percent of waste production.

Table 1
Relevant studies in sustainable closed-loop SCND.

Articles	Model	Sustainability dimension	Solution approaches	Recyclable Item
Subulan et al. (2015a)	MILP	Economic Environmental	Exact	Tire
Kannegiesser et al. (2015)	MILP	Economic Environmental Social	Exact	–
Subulan et al. (2015b)	MILP	Economic Environmental	Exact	Battery
Soleimani and Kannan (2015)	MILP	Economic	Metaheuristic	–
Das and Posinasetti, 2015	MILP	Economic Environmental	Exact	MIG welder
Zhalechian et al. (2016)	MINLP	Economic Environmental Social	Metaheuristic	LED and LCD Televisions
Tahirov et al. (2016)	MILP	Economic Environmental Social	Exact	–
Talaei et al. (2016)	MILP	Economic Environmental	Exact	Electronics products
Soysal (2016)	MILP	Economic	Metaheuristic	Soft drink glass
Tsao et al. (2016)	CA	Economic	Exact	–
Mohajeri and Fallah (2016)	ILP	Economic Environmental	Exact	–
Tiwari et al. (2016)	MILP	Economic Environmental	Metaheuristic	–
Zohal and Soleimani (2016)	ILP	Economic Environmental	Metaheuristic	Gold
Gaur et al. (2017)	MINLP	Economic	Heuristic	Battery
Amin et al. (2017)	ILP	Economic	Exact	Tire
Soleimani et al. (2017)	MILP	Economic Environmental Social	Metaheuristic	–
Sgarbossa, and Russo (2017)	MILP	Economic Environmental Social	Exact	Food
He (2017)	ILP	Economic	Exact	–
Pedram et al. (2017)	MILP	Economic	Exact	Tire
Arampantzi and Minis (2017)	MILP	Economic Environmental Social	Exact	–
Nurjanni et al. (2017)	MILP	Economic Environmental	Exact	Electronic services
Zhou et al. (2017)	ILP	Economic Environmental	Exact	–
Banasik et al. (2017)	MILP	Economic Environmental	Exact	Mushroom
Babazadeh et al. (2017)	MILP	Economic Environmental	Exact	Biodiesel
Kadambala et al. (2017)	MILP	Economic Environmental	Metaheuristic	–
Bazan et al. (2017)	ILP	Economic Environmental	Exact	–
Paydar et al. (2017)	MILP	Economic	Exact	Engine oil
Mohammed et al. (2017)	MILP	Economic Environmental	Exact	–
Heydari et al. (2017)	CA	Economic Environmental	Exact	–
Fard and Hajiaghaei-Keshteli (2018)	MILP	Economic	Metaheuristic	Glass
This study	MILP	Economic Environmental Social	Hybrid Metaheuristic	Tire

Distributers (j) purchase the tire type p from manufacturer m with price PC_{mp}^{MP} and distribute in market (l) with price PC_{jp}^{J} according to the markets' demand d_{lp}. In the reverse flow, the potential collector center (n) collect α_{lp} percentages of the scraped tires (p) with price PC_{lp}^{L} from market (l). 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 plant or other industry with price PC_{r}^{R}. In addition, to recycle the products, different type of technology (c) is existed which has a special waste production percent rate (U_c). The proposed model aims to determine the locations of the facilities as well as forward and revers flows through tire supply chain by considering sustainability dimensions. To this end the sustainability dimensions are modeled as follow:

- *Economic dimension*

In the term of economic dimension, the proposed model minimizes the total cost of network including fixed opening cost, variable cost, transportation cost, and purchasing cost. Hence the model determines the location of the facilities and allocates the right amount of products or raw material to them such that the total cost of the network is minimized.

- *Environmental dimension*

To formulate the environmental impact of tire closed-loop supply chain, LCA-based methodology is adopted. The LCA methodology is a technique to evaluate the environmental dimensions associated with all stages of a products life from raw material

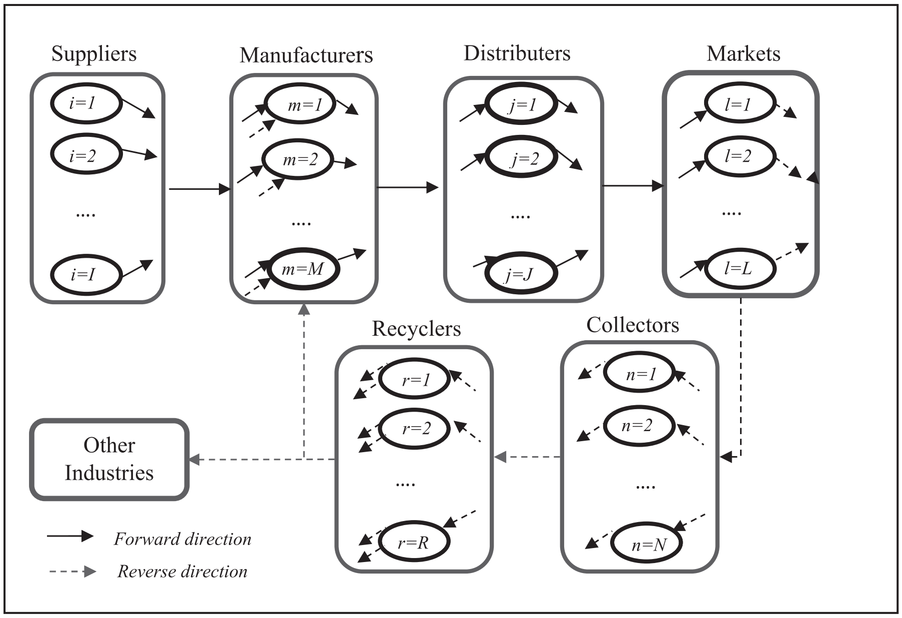

Fig. 1. Tire closed-loop supply chain network.

extraction processing, manufacturing, distribution, using, repairing and recycling. This methodology can be formulated by two subsections: effect of supply chain network on environment and effect of products after using. Govindan et al. (2016) utilized the LCA-methodology for designing the reverse supply chain network by considering the effect of manufacturing products on environment, impacts of products ecosystem quality, and resource of products (raw materials). In this regard, they developed a mixed integer linear programming to formulate environmental dimension. In other research, Zohal and Soleimani (2016) employed LCA-methodology in gold industry by considering only the effect of supply chain model on environment including emissions of manufacturing and recycling, and transportation system. Bouzon et al. (2017) developed LCA-methodology for reverse logistic network in Brazil. In their method, emission of transportation system and recycling of products were minimized.

The LCA framework was used by International Standard Organization (ISO) to develop ISO 14000 environmental management (Pishvaee et al., 2014). Here, to measure the environmental impact of the tire in closed-loop supply chain, the ReCiPe 2008 database is used (Goedkoop et al., 2009). Because of the ReCiPe 2008 database considers both mid-point and end-point of products completely (Pishvaee et al., 2014). Four environmental factors including facilities opening, processing of tire, transportation, and released tire in nature were estimated according to human health and ecosystem diversity index (Govindan et al., 2014). Two indices are combined in weighted manner (i.e. 70% and 30% for human health and ecosystem diversity) for estimating facilities opening, processing of tire according to technologies, and transportation environmental impact. While the environmental impact of the released tire in nature were estimated based on the 20% and 80% combination of the human health and ecosystem diversity respectively (Babbar and Amin, 2018). To this end, the ReCiPe 2008 database of the ECO-it software (http://www.pre.nl/eco-it) was used to estimate environmental impact.

In this regards, the environmental impact of opening a facility in potential locations (including manufacturing plant by using manufacturing technology type t (EO^M_{mt}), distributing center (EO^J_j), collecting center (EO^N_n), recycling plant by using recycling technology type c (EO^R_{rc})), the environmental impact of processing a unit of the product p at each facility (including manufacturing plant by using manufacturing technology type t (EM^M_{mpt}), distributing center (EM^J_{jp}), collecting center (EM^N_{np}), recycling plant by using recycling technology type c (EM^R_{rc})), and the environmental impact of transportation between facilities (*i.e.* supplier and manufacturer (EH^{IM}_{im}), manufacturer and distributer (EH^{MJ}_{mj}), distributer and market (EH^{JL}_{jl}), market and collector (EH^{LN}_{ln}), collector and recycler (EH^{NR}_{nr}), and recycler and manufacturer (EH^{RM}_{rm})). Furthermore the impact of released scraped tire (type p) on environment that weren't collected by collector centers is considered with ED_p.

- *Social dimension*

The social dimension can be defined as a continued commitment for each business to behave ethically and improve the quality of humans' life. It has been investigated by several impacts of supply chain network related to social dimensions in the recent decades (De Brito, 2003). According to the product types, these factors may be not same for all supply chain networks (Dehghanian and Mansour, 2009). Devika et al. (2014) studied the job opportunities and work injuries dimensions for glass industry. Zhalechian et al. (2016) considered the impact of job opportunities with the rate of unemployment and balanced economic developments for LED and LCD TVs industry. Nematollahi et al. (2017) proposed a social collaborative decision-making with a supplier and a retailer. In their model, the quality of service level was evaluated for considering social impact of network.

To estimate the social impact of the supply chain, different frameworks can be found in the literature. Pishvaee et al. (2014) comprised different social impact analysis method and guidelines. They used guideline for social life cycle assessment of product introduced by Beno ıt and Mazijn (2009) and social responsibility-ISO 26000 (ISO, 2010) to estimate the social impact of their supply chain. According to the guideline for social life cycle assessment of product, we determine the life cycle stages of the tire closed-loop supply chain as follows:

- Manufacturing and recycling processing technologies
- Manufacturing and recycling establishment locations and capacities
- Distributing and collecting process of material flows between facilities

Scholars utilized different factors to assess the social impact of each stage considering different guidelines and methods. Pishvaee et al. (2014) comprised the social impact factors of different methods such as labor practices, the environment, consumer issues and community involvement and development. This study by considering SA8000 guideline (SAI, 2008) uses job opportunities and workers' safety to assess the social impact of the tire closed-loop supply chain. The job opportunities not only cover the labor practices but also consider the community involvement and development. The workers' safety indicates the human rights and fair operating practices. However, both factors should be estimated in two periods including establishment and utilization. There isn't any available software or database to estimate the social impacts. So, the external experts have been employed to estimate the weights and amount of each parameter. To this end, we use the pairwise comparison matrix for determining the weight of each factors. However more comprehensive analyses on these standard guidelines are needed to be explored (Pishvaee et al., 2014).

As mentioned earlier, the job opportunities and work injuries factors are considered to formulate the social dimension. Here, the job opportunities are divided into two categories consisting of the fixed job opportunities of facilities $FJ_{\square}^{\square}$ (not depend on the capacity of a facility such as official personnel) and variable job opportunities of opened facilities $VJ_{\square}^{\square}$ (depend on the capacity of a facility and amount of products). As the second factor, work injuries might occurring at the establishment period in the facilities (*i.e.* the loss of days caused work injuries at establishment period in manufacturing plant by using manufacturing technology type t (FL_{mt}^{M}), distributing center (FL_{j}^{J}) collecting center (FL_{n}^{N}), and recycling plant by using recycling technology type c (FL_{rc}^{R})) or during utilization of the facilities (i.e. the loss of days caused work injuries of product (p) during manufacturing process by using manufacturing technology type t (VL_{mpt}^{M}), distributing process (VL_{jp}^{J}), collecting process (VL_{np}^{N}), and recycling process by using recycling technology type c (VL_{rpc}^{R})).

3.1. Assumptions

The following assumptions were considered for the problem formulation:

- The demand of each customer must to be met.
- Each facility can be assigned to more than one facility at another level.
- The potential locations for facilities in each level are predefined.
- Between facilities in each level no flows are existed.
- The capacity of each facility in each location is limited.
- A part of distributed tires in markets were collected after utilization as scrapped tire.
- The raw material price of the recyclers is less than supplier.
- For manufacturers and recyclers, different type of technologies has been considered. These technologies have specific costs, environmental emissions and social impacts as well as different rates for waste production.

3.2. Notations

The following indices, parameters and variables were used to formulate the problem:

Indices:	
i	Index of suppliers, $i \in \{1, 2, ..., I\}$
m	Index of potential manufacturing plant location, $m \in \{1, 2, ..., M\}$
j	Index of potential distribution center location, $j \in \{1, 2, ..., J\}$
l	Index of market zones, $l \in \{1, 2, ..., L\}$
n	Index of potential collecting center location, $n \in \{1, 2, ..., N\}$
r	Index of potential recycler plant location, $r \in \{1, 2, ..., R\}$
p	Index of tire type,$p \in \{1, 2, ..., P\}$
t	Index of manufacturing technologies, $t \in \{1, 2, ..., T\}$
c	Index of recycling technologies, $c \in \{1, 2, ..., C\}$
o	other industry
Parameters:	
TC_{im}^{IM}	Transportation cost per unit form supplier i and manufacturer m
TC_{mjp}^{MJ}	Transportation cost per unit for tire type p from manufacturer m and distributer j
TC_{jlp}^{JL}	Transportation cost per unit for tire type p from distributer j and market l
$TC_{\ln p}^{LN}$	Transportation cost per unit for tire type p form market l and collector n
TC_{nrp}^{NR}	Transportation cost per unit for tire type p form collector n and recycler r
TC_{rm}^{RM}	Transportation cost per unit form recycler r and manufacturer m
TC_{ro}^{RO}	Transportation cost per unit from recycle r and other application o
FC_{mt}^{M}	Fixed opening cost of manufacturer m by using manufacturing technology t to be established
FC_{j}^{J}	Fixed opening cost of distributer j to be established
FC_{n}^{N}	Fixed opening cost of collector n to be established
FC_{r}^{R}	Fixed opening cost of recycler r by using recycling technology c to be established
MC_{mpt}^{M}	Variable manufacturing cost per unit for tire type p and manufacturer m by using manufacturing technology t
MC_{jp}^{J}	Variable distributing cost per unit for tire type p and distributer j
MC_{np}^{N}	Variable collecting cost per unit for tire type p and collector n
MC_{rc}^{R}	Variable recycling cost for recycler r by using recycling technology c
PC_{i}^{I}	Cost of purchasing raw material for all types of tires from supplier i

(*continued*)

PC^{M}_{mp}	Cost of purchasing tire type p from manufacturer m
PC^{J}_{jp}	Cost of purchasing tire type p from distributer j
PC^{N}_{np}	Cost of purchasing tire type p from collector n
PC^{R}_{r}	Cost of purchasing recycled tires from recycler r
MAX^{M}	Maximum desired number of established sites for manufacturers
MAX^{J}	Maximum desired number of established sites for distributers
MAX^{N}	Maximum desired number of established sites for collectors
MAX^{R}	Maximum desired number of established sites for recyclers
d_{lp}	Demand of market l for tire type p
α_{lp}	Fraction of used tires type p returned from market l.
B_{pt}	Rate of the percent of waste production for manufacturing technology type t and tire type p
U_{c}	Rate of the percent of waste production for recycling technology type c
CAP^{I}_{i}	Capacity of supplier i
CAP^{M}_{mp}	Capacity of manufacturer m for tire type p
CAP^{J}_{jp}	Capacity of distributer j for tire type p
CAP^{N}_{np}	Capacity of collector n for tire type p
CAP^{R}_{r}	Capacity of recycler r
EO^{M}_{mt}	Environmental impact of establishing manufacturer m by using manufacturing technology t
EO^{N}_{n}	Environmental impact of establishing collector n
EO^{J}_{j}	Environmental impact of establishing distributer j
EO^{R}_{rc}	Environmental impact of establishing recycler r by using recycling technology c
EM^{M}_{mpt}	Per unit environmental impact of manufacturing plant for manufacturer m and tire type p by using manufacturing technology t
EM^{J}_{jp}	Per unit environmental impact of distributing for distributer j and tire type p
EM^{N}_{np}	Per unit environmental impact of collecting for collector n and tire type p
EM^{R}_{rc}	Per unit environmental impact of recycling for recycler r by using recycling technology c
EH^{IM}_{im}	Per unit environmental impact of transportation system between supplier i and manufacturer m
EH^{MJ}_{mj}	Per unit environmental impact of transportation system between manufacturer m and distributer j
EH^{JL}_{jl}	Per unit environmental impact of transportation system between distributer j and market l
$EH^{LN}_{\ln}$	Per unit environmental impact of transportation system between market l and collector n
EH^{NR}_{nr}	Per unit environmental impact of transportation system between collector n and recycler r
EH^{RM}_{rm}	Per unit environmental impact of transportation system between recycler r and manufacturer m
EH^{RO}_{ro}	Per unit environmental impact of transportation system between recycler r and other industry application o
ED_{p}	Environmental impact of released tire type p on the environment
W_{H} and W_{D}	Given weights to the elements of environmental impacts objective: (1) transportation and opening emissions and (2) scraped tires, respectively.
FJ^{M}_{m}	The number of fixed job opportunities (*i.e.* managerial positions) created by establishing manufacturer m by using manufacturing technology t
FJ^{J}_{j}	The number of fixed job opportunities created by establishing distributer j
FJ^{N}_{n}	The number of fixed job opportunities created by establishing collector n
FJ^{R}_{rc}	The number of fixed job opportunities created by establishing recycler r by using recycling technology c
VJ^{M}_{mt}	The number of variable job opportunities (*i.e.* line workers) created through manufacturing plant at center m by using manufacturing technology t
VJ^{J}_{j}	The number of variable job opportunities created through working of distributer j
VJ^{N}_{n}	The number of variable job opportunities created through working of collector n
VJ^{R}_{rc}	The number of variable job opportunities created through working of recycler r by using recycling technology c
FL^{M}_{mt}	The lost days cost from work's damages during the establishment of manufacturer m by using manufacturing technology t
FL^{J}_{j}	The lost days cost from work's damages during the establishment of distributer j
FL^{N}_{n}	The lost days cost from work's damages during the establishment of collector n
FL^{R}_{rc}	The lost days cost from work's damages during the establishment of recycler r by using recycling technology c
VL^{M}_{mpt}	The lost of days caused work's damages during the manufacturing tire p at manufacturer m by using manufacturing technology t
VL^{J}_{jp}	The lost of days caused work's damages during the handling of tire type p at distributer j
VL^{N}_{np}	The lost of days caused work's damages during the handling of tire type p at collector n
VL^{R}_{rc}	The lost of days caused work's damages during the handling of products at recycler r by using recycling technology c
E_{L} and E_{D}	The weights given to the elements of social impacts objective: (1) created job opportunities, and (2) worker's lost days, respectively.
Decision variables:	
X^{IM}_{im}	Amount of products flow between supplier i and manufacturer m
X^{RM}_{rmc}	Amount of products flow between recycler r by recycling technology type c and manufacturer m
X^{RO}_{roc}	Amount of products flow between recycler r by recycling technology type c and other industry applications o
X^{MJ}_{mjpt}	Amount of tires type p transformed between manufacturer m by manufacturing technology type t and distributer j
X^{JL}_{jlp}	Amount of tires type p transformed between distributer j and market l
$X^{LN}_{\ln p}$	Amount of returned tires type p transformed between market l and collector n
X^{NR}_{nrp}	Amount of reused tires type p transformed between collector n and recycler r
Y^{M}_{mt}	1 if manufacturer m by using manufacturing technology type t is to be established, otherwise 0
Y^{J}_{j}	1 if distributer j is to be established, otherwise 0
Y^{N}_{n}	1 if collector n is to be established, otherwise 0
Y^{R}_{rc}	1 if recycler r by using recycling technology type c is to be established, otherwise 0

3.3. Mathematical model

The proposed multi-objective mixed integer linear programming model of sustainable tire closed-loop supply chain problem is as follow:

- *Economic Objective function:*

$$MinZ_1 = Z_1^{FC} + Z_1^{VC} + Z_1^{TC} + Z_1^{PC} \quad (1)$$

The economic dimension of the sustainable tire closed loop supply chain network is optimized by equation (1) including: Equation (1-1) fixed cost of opening facilities; Equation (1-2) the variable cost for manufacturing, distributing, collecting, and recycling; Equation (1-3) the transportation costs between each level; Equation (1-4): the purchasing costs of network.

- *Environmental objective function:*

$$MinZ_2 = W_H \times \left(Z_2^{EO} + Z_2^{EM} + Z_2^{EH}\right) + W_D \times Z_2^{ED} \quad (2)$$

The objective function (2) optimized the environmental impact of the proposed sustainable closed loop tire supply chain model. In equation (2), the impact of opening cost and transportation system were weighted byW_H. Also, the impact of released scraped tires in the nature is weighted byW_D. The environmental impact of network has been formulated with Equation (2-1) environmental impacts of the facilities establishment; Equation (2-2) the environmental impacts of the manufacturing, distributing, collecting, and recycling; Equation (2-3) the environmental impact of transportation systems; Equation (2-4) the environmental impact of dropped up scraped tire.

$$Z_1^{FC} = \sum_{m=1}^{M}\sum_{t=1}^{T} FC_{mt}^{M} \times Y_{mt}^{M} + \sum_{j=1}^{J} FC_j^{J} \times Y_j^{J} + \sum_{n=1}^{N} FC_n^{N} \times Y_n^{N} + \sum_{r=1}^{R}\sum_{c=1}^{C} FC_{rc}^{R} \times Y_{rc}^{R} \quad (1\text{-}1)$$

$$Z_1^{VC} = \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{t=1}^{T} MC_{mpt}^{M}\left(\sum_{j=1}^{J} X_{mjpt}^{MJ} \times (1-B_{pt})\right) + \sum_{j=1}^{J}\sum_{p=1}^{P} MC_{jp}^{J} \quad \sum_{l=1}^{L} X_{jlp}^{JL}) + \sum_{n=1}^{N}\sum_{p=1}^{P} MC_{np}^{N} \quad \sum_{l=1}^{L} X_{lnp}^{LN}) + \sum_{r=1}^{R}\sum_{c=1}^{C} MC_{rc}^{R}\left(\sum_{m=1}^{M} X_{rmc}^{RM} + X_{roc}^{RO}\right) \times (1-U_c) \quad (1\text{-}2)$$

$$Z_1^{TC} = \sum_{i=1}^{I}\sum_{m=1}^{M} TC_{im}^{IM} \times X_{im}^{IM} + \sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{p=1}^{P} TC_{mjp}^{MJ} \times \quad \sum_{t=1}^{T} X_{mjpt}^{MJ} \times (1-B_{pt})) + \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{p=1}^{P} TC_{jlp}^{JL} \times X_{jlp}^{JL} + \sum_{l=1}^{L}\sum_{n=1}^{N}\sum_{p=1}^{P} TC_{lnp}^{LN} \times X_{lnp}^{LN} + \sum_{n=1}^{N}\sum_{r=1}^{R}\sum_{p=1}^{P} TC_{nrp}^{NR} \times X_{nrp}^{NR} + \sum_{r=1}^{R}\sum_{m=1}^{M} TC_{rm}^{RM} \times \quad \sum_{c=1}^{C} X_{rmc}^{RM} \times (1-U_c)) + \sum_{r=1}^{R} TC_{ro}^{RO} \times \left(\sum_{c=1}^{C} X_{roc}^{RO} \times (1-U_c)\right) \quad (1\text{-}3)$$

$$Z_1^{PC} = \sum_{i=1}^{I} PC_i^{I} \quad \sum_{m=1}^{M} X_{im}^{IM}) + \sum_{m=1}^{M}\sum_{p=1}^{P} PC_{mp}^{M}\left(\sum_{j=1}^{J}\sum_{t=1}^{T} X_{mjpt}^{MJ} \times (1-B_{pt})\right) + \sum_{j=1}^{J}\sum_{p=1}^{P} PC_{jp}^{J} \quad \sum_{l=1}^{L} X_{jlp}^{JL}) + \sum_{n=1}^{N}\sum_{p=1}^{P} PC_{np}^{N}\left(\sum_{l=1}^{L} X_{lnp}^{LN}\right) - \sum_{r=1}^{R} PC_r^{R} \quad \sum_{m=1}^{M}\sum_{c=1}^{C} X_{rmc}^{RM} \times (1-U_c)) \quad (1\text{-}4)$$

$$Z_2^{EO} = \sum_{m=1}^{M}\sum_{t=1}^{T} EO_{mt}^{M} \times Y_{mt}^{M} + \sum_{j=1}^{J} EO_j^{J} \times Y_j^{J} + \sum_{n=1}^{N} EO_n^{N} \times Y_n^{N} + \sum_{r=1}^{R}\sum_{c=1}^{C} EO_{rc}^{R} \times Y_{rc}^{R} \quad (2\text{-}1)$$

$$Z_2^{EM} = \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{t=1}^{T} EM_{mpt}^{M}\left(\sum_{j=1}^{J} X_{mjpt}^{MJ} \times (1-B_{pt})\right) + \sum_{j=1}^{J}\sum_{p=1}^{P} EM_{jp}^{J} \quad \sum_{l=1}^{L} X_{jlp}^{JL}) + \sum_{n=1}^{N}\sum_{p=1}^{P} EM_{np}^{N} \quad \sum_{l=1}^{L} X_{lnp}^{LN}) + \sum_{r=1}^{R}\sum_{c=1}^{C} EM_{rc}^{R}\left(\sum_{n=1}^{N} X_{rmc}^{RM} + X_{roc}^{RO}\right) \times (1-U_c) \quad (2\text{-}2)$$

$$Z_2^{EH} = \sum_{i=1}^{I}\sum_{m=1}^{M} EH_{im}^{IM} \times X_{im}^{IM} + \sum_{m=1}^{M}\sum_{j=1}^{J} EH_{mj}^{MJ} \times \left(\sum_{p=1}^{P}\sum_{t=1}^{T} X_{mjpt}^{MJ}(1-B_{pt})\right) + \sum_{j=1}^{J}\sum_{l=1}^{L} EH_{jl}^{JL} \times \left(\sum_{p=1}^{P} X_{jlp}^{JL}\right) + \sum_{l=1}^{L}\sum_{n=1}^{N} EH_{ln}^{LN} \times \left(\sum_{p=1}^{P} X_{lnp}^{LN}\right) + \sum_{r=1}^{R}\sum_{n=1}^{N} EH_{nr}^{NR} \times \left(\sum_{p=1}^{P} X_{nrp}^{NR}\right) + \sum_{r=1}^{R}\sum_{m=1}^{M} EH_{rm}^{RM} \times \left(\sum_{c=1}^{C} X_{rmc}^{RM} \times (1-U_c)\right) + \sum_{r=1}^{R} EH_{ro}^{RO} \times \left(\sum_{c=1}^{C} X_{roc}^{RO} \times (1-U_c)\right) \tag{2-3}$$

$$Z_2^{ED} = \sum_{p=1}^{P} ED_p \times \left(\sum_{l=1}^{L}\left(\sum_{j=1}^{J} X_{jlp}^{JL} - \sum_{n=1}^{N} X_{lnp}^{LN}\right)\right) \tag{2-4}$$

- *Social objective function:*

$$MaxZ_3 = E_L \times \left(Z_3^{FJ} + Z_3^{VJ}\right) - E_D \times \left(Z_3^{FL} + Z_3^{VL}\right) \tag{3}$$

Equation (3) optimizes the social dimension of the proposed model including the weights of job opportunities and worker's lost days by $E_L$and E_D, respectively. Equations (3-1) and (3-2) consider the fixed and variable job opportunities for supply chain network. Moreover, equations (3-3) and (3-4) are the fixed lost days for work during the establishment of facilities and the loss of days caused work's damages during the manufacturing and distributing, collecting and recycling.

$$\sum_{i=1}^{I} X_{im}^{IM} + \sum_{r=1}^{R}\sum_{c=1}^{C} X_{rmc}^{RM} \times (1-U_c) = \sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T} X_{mjpt}^{MJ} \times (1-B_{pt}) \quad \forall m \tag{4}$$

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{t=1}^{T} X_{mjpt}^{MJ} = \sum_{l=1}^{L}\sum_{p=1}^{P} X_{jlp}^{JL} \quad \forall j \tag{5}$$

$$\sum_{j=1}^{J} X_{jlp}^{JL} = d_{lp} \quad \forall l,p \tag{6}$$

$$Z_3^{FJ} = \sum_{m=1}^{M}\sum_{t=1}^{T} FJ_{mt}^{M} \times Y_{mt}^{M} + \sum_{j=1}^{J} FJ_j^{J} \times Y_j^{J} + \sum_{n=1}^{N} FJ_n^{N} \times Y_n^{N} + \sum_{r=1}^{R}\sum_{c=1}^{C} FJ_{rc}^{R} \times Y_{rc}^{R} \tag{3-1}$$

$$Z_3^{VJ} = \sum_{m=1}^{M}\sum_{t=1}^{T} VJ_{mt}^{M} \times \left(\sum_{j=1}^{J}\sum_{p=1}^{P} X_{mjpt}^{MJ} \times (1-B_{pt}) \Big/ CAP_{mp}^{M}\right) + \sum_{j=1}^{J} VJ_j^{J} \times \left(\sum_{l=1}^{L}\sum_{p=1}^{P} X_{jlp}^{JL} \Big/ CAP_{jp}^{J}\right) + \sum_{n=1}^{N} VJ_n^{N} \times \left(\sum_{l=1}^{L}\sum_{p=1}^{P} X_{lnp}^{LN} \Big/ CAP_{np}^{N}\right) + \sum_{r=1}^{R}\sum_{c=1}^{C} VJ_{rc}^{R} \times \left(\sum_{m=1}^{M}\left(X_{rmc}^{RM} + X_{roc}^{RO}\right) \times (1-U_c)/CAP_r^{R}\right) \tag{3-2}$$

$$Z_3^{FL} = \sum_{m=1}^{M}\sum_{t=1}^{T} FL_{mt}^{M} \times Y_{mt}^{M} + \sum_{j=1}^{J} FL_j^{J} \times Y_j^{J} + \sum_{n=1}^{N} FL_n^{N} \times Y_n^{N} + \sum_{r=1}^{R}\sum_{c=1}^{C} FL_{rc}^{R} \times Y_{rc}^{R} \tag{3-3}$$

$$Z_3^{VL} = \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{t=1}^{T} VL_{mpt}^{M} \times \left(\sum_{j=1}^{J} X_{mjpt}^{MJ} \times (1-B_{pt}) \Big/ CAP_{mp}^{M}\right) + \sum_{j=1}^{J}\sum_{p=1}^{P} VL_{jp}^{J} \times \left(\sum_{l=1}^{L} X_{jlp}^{JL} \Big/ CAP_{jp}^{j}\right) + \sum_{n=1}^{N}\sum_{p=1}^{P} VL_{np}^{N} \times \left(\sum_{l=1}^{L} X_{lnp}^{LN} \Big/ CAP_{np}^{N}\right) + \sum_{r=1}^{R}\sum_{c=1}^{C} VL_{rc}^{R} \times \left(\sum_{m=1}^{M}\left(X_{rmc}^{RM} + X_{roc}^{RO}\right) \times (1-U_c)/CAP_r^{R}\right) \tag{3-4}$$

- Constraints:

Constraints (4) to (8) guarantee the flow of products through the network.

$$\sum_{l=1}^{L} X_{lnp}^{LN} = \sum_{r=1}^{R} X_{nrp}^{NR} \quad \forall n,p \tag{7}$$

$$\sum_{n=1}^{N}\sum_{p=1}^{P} X_{nrp}^{NR} = \sum_{m=1}^{M}\sum_{c=1}^{C}\left(X_{rmc}^{RM} + X_{roc}^{RO}\right) \times (1 - U_c) \tag{8}$$

Equation (9) ensures that only a part of scarped tires (a_{lp}) could be collected by collectors from each market.

$$\sum_{n=1}^{N} X_{\ln p}^{LN} \le a_{lp} \times d_{lp} \quad \forall l, p \tag{9}$$

The capacities of suppliers were considered in constraints (10).

$$\sum_{m=1}^{M} X_{im}^{IM} \le CAP_i^I \quad \forall i \tag{10}$$

Equations (11)–(14) ensure that if manufacturers, distributers, collectors, and recyclers facilities were opened, it cannot be allocated more than their capacity.

$$\sum_{j=1}^{J} X_{mjpt}^{MJ} \times (1 - B_{pt}) \le CAP_{mp}^{M} \times Y_{mt}^{M} \quad \forall m, p, t \tag{11}$$

$$\sum_{l=1}^{L} X_{jlp}^{JL} \le CAP_{jp}^{J} \times Y_j^J \quad \forall j, p \tag{12}$$

$$\sum_{l=1}^{L} X_{\ln p}^{LN} \le CAP_{np}^{N} \times Y_n^N \quad \forall n, p \tag{13}$$

$$\sum_{m=1}^{M} X_{rmc}^{RM} + X_{roc}^{RO} \le CAP_r^R \times Y_{rc}^R \quad \forall r, c \tag{14}$$

Equations (15) and (16) determine that only one technology should be assigned for manufacturers and recyclers.

$$\sum_{t=1}^{T} Y_{mt}^{M} = 1 \quad \forall m \tag{15}$$

$$\sum_{c=1}^{C} Y_{rc}^{R} = 1 \quad \forall r \tag{16}$$

The number of opened facilities in each level is restricted by constraints (17) to (20).

$$\sum_{m=1}^{M} Y_{mt}^{M} \le MAX^M \quad \forall t \tag{17}$$

$$\sum_{j=1}^{J} Y_j^J \le MAX^J \tag{18}$$

$$\sum_{n=1}^{N} Y_n^N \le MAX^N \tag{19}$$

$$\sum_{r=1}^{R} Y_{rc}^{R} \le MAX^R \quad \forall c \tag{20}$$

Finally, Constraints (21) and (22) enforce the binary and non-negativity restrictions on corresponding decision variables.

$$Y_{mt}^{M},\ Y_j^J,\ Y_n^N,\ Y_{rc}^{R} \in \{0,\ 1\} \tag{21}$$

$$X_{im}^{IM}, X_{rmc}^{RM}, X_{roc}^{RO}, X_{mjpt}^{MJ}, X_{jlp}^{JL}, X_{\ln p}^{LN}, X_{njp}^{NJ}, X_{nrp}^{NR} \ge 0 \tag{22}$$

4. Solution approach

Various types of hybrid metaheuristic algorithms have been developed to solve the NP-*hard* problems. For example, Dib et al. (2015) proposed a hybrid algorithm of Variable Neighborhood Search (VNS) and Genetic Algorithm (GA) in which GA was utilized as the main loop and VNS improve the local searches as a sub-loop. Lin et al. (2015) combined the Artificial Immune Algorithm (AIA) with Differential Evolution (DE) in which AIA maintains the exploitation properties and DE improves the exploration phase. Recently, Li et al. (2017) presented a comprehensive review of metaheuristic algorithms. They emphasized that hybrid metaheuristic algorithms can be more efficient than the general ones. Combining algorithms to a hybrid one leads an intelligence search engine for performing the exploration and exploitation phases more efficiently (Shirazi et al., 2010; Li et al., 2017).

This study develops four hybrid metaheuristic algorithms aiming to improve the solution quality and decrease the computational time. Five well-known metaheuristic algorithms including Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TS), Red Deer Algorithm (RDA), and Water Wave Optimization (WWO) are developed and evaluated to explore the strangeness and weakness of them for solving the sustainable closed-loop tire supply chain network. By utilizing the advantages of each algorithm for solving large sustainable tire closed-loop supply chain network problem, four new hybrid metaheuristic algorithms are developed. The main features and pseudo code of the algorithms are presented in Supplementary material S.1 to S.5. Since the proposed sustainable closed-loop tire SCND problem is a multi-objective problem, the whole metaheuristic algorithms are developed to find Pareto optimal solutions.

4.1. Solution representation

To reduce the running cost of the algorithms, many researchers decided on how to represent the solutions and relate them to searching space efficiently (Torabi et al., 2013; Ding et al., 2017). To this end, two kinds of solution representation were utilized including the priority-based representation (Gen et al., 2006) and the transportation matrix representation (Devika et al., 2014). In each of them, two solution representation method were used for binary ($Y_{\square}^{\square}$) and integer ($X_{\square}^{\square}$) decision variables simultaneously. Furthermore, the initial solutions are generated by Random-Key (*RK*) that could be used in search space by various operators (Snyder and Daskin, 2006). To convert the initial solutions into feasible ones, the procedure proposed by Sadeghi-Moghaddam et al. (2017) is used. The proposed hybrid metaheuristic algorithms are solved by both solution representation methods and the results are compared to show the performance of solution representation to encounter with large scale networks. The details of the Priority-based representation (pri) and transportation matrix representation (tra) are described in Supplementary material S.6 and S.7.

4.2. Hybrid of RDA & SA (H-RS)

RDA is a population based algorithm and includes several steps (see Supplementary material S.1). The hybrid RDA & SA (H-RS) is developed to reduce the computational time and eliminate some steps by replacing the SA rules. The H-RS enhance the exploitation properties by a simple SA sub-loop. In this regard, an intelligence interaction between the exploitation and exploration phases is implemented in the proposed H-RS. Therefore RDA and SA algorithms are hybridized in which RDA plays as a main loop and SA improves the characteristic of intensification phase by considering SA rule instead of roaring operator in RDA. Fig. 2 shows the pseudo code of the proposed hybrid algorithm in details.

4.3. Hybrid of WWO & GA (H-WG)

The proposed hybrid WWO & GA (H-WG) enhanced the exploration characteristics to make an efficient trade-off between the

```
Initialize the Red Deers population.
Calculate the fitness and sort them and form the hinds (N_hind) and male RDs (N_male).
Set the Pareto optimal fronts.
while (t< maximum number of iteration)
    for each male RD
      sub=1;
      while (sub< maximum number of sub-iteration)
            Create a neighbor of this solution by a procedure which is depicted in Fig. S.3.2 from Supplementary material S.3.
            if the new solution is better than prior
                Replace the old solution by new solution.
            else
                Compute δ, δ = |f_old − f_new|.
                if rand< exp(−δ/T)
                   Replace the new solution.
                endif
            endif
      sub=sub+1;
      endwhile
    endfor
    Update T.
    Sort the males and also form the stags and the commanders.
    Form harems: (V_n = v_n − max_i{v_i}; P_n = | V_n / Σ_{i=1}^{N_Com} V_i |; N.harem_n = round{P_n.N_hind}).
    for each male commander
      Mate male commander with the selected hinds of his harem randomly.
      new = (com+hind)/2;
      Select a harem randomly and name it k.
      Mate male commander with some of the selected hinds of the harem.
    end for
    for each stag
      Calculate the distance between the stag and all hinds and select the nearest hind.
      new = (stag+hind)/2;
      Mate stag with the selected hind.
    end for
    Select the next generation with roulette wheel selection.
    Update the Pareto optimal solutions.
    t=t+1
end while
Consider the best front and evaluate the solutions by assessment metrics.
```

Fig. 2. The pseudo-code of a multi-objective H-RS.

intensification and diversification phases. While the WWO algorithm uses a strong exploitation mechanism, its exploration procedure seems weak (Wu et al., 2017). The random solutions are generated in iterations and then are replaced by new ones randomly in the propagation operator of the WWO. The evolutionary concept used in GA is used for selecting and replacing solutions in iterations. In this regard, two solutions among all solutions are selected by roulette wheel selection procedure. Then crossover operator is used to generate two new solutions for preparing a new generation. The pseudo-code of the proposed H-WG algorithm is presented in Fig. 3.

4.4. Hybrid of WWO & TS (H-WT)

The proposed hybrid WWO & TS (H-WT) changes the search operators to find the potential zones in search space and used an adopted memory from TS to increase the exploitation properties of the WWO. As presented in Supplementary material S.2, WWO uses three different operators considering the shallow water wave models. In H-WT the mutation procedures are used instead of the propagation operator to enhance the search engine of the general WWO. In addition, the breaking operator in WWO is changed by the main characteristic from TS to use an adopted memory. The details of the developed H-WT algorithm are illustrated by a pseudo-code as given in Fig. 4.

4.5. Hybrid of RDA & WWO (H-RW)

The hybrid RDA & WWO (H-RW) reduces the computational time of RDA by eliminating some steps and also generates a strong interaction between the phases. H-RW is developed using the advantages of WWO in intensification phase and RDA in diversification phase. Using a modified propagation operator of WWO instead of roaring and fighting operators of RDA is suggested. The pseudo-code of the H-RW is presented in Fig. 5.

5. Experimental evaluation

To evaluate the performance of the proposed hybrid meta-heuristic algorithms for solving sustainable tire closed loop SCND problem, nine test problems are generated in three scales *i.e.* small, medium and large size. In each scale ten test problems are generated randomly (total 90 test problems). The details of each test problem are reported in Tables 2 and 3. Furthermore, the

```
Set the parameters.
Initialize a random population P of n waves.
Select a crossover procedure as illustrated in Fig. S.3.1 from Supplementary material S.3.
Form the initial Pareto optimal fronts.
X*=the best solution.
while (t< maximum number of iteration)
    for each x ∈ P
        Select two solutions by roulette wheel selection.
        Apply crossover and generate two solutions.
        The best solution among two new solutions is selected as x'
        if f(x') is better than f(x)
         if f(x') is better than f(X*)
          /*break x'*/
          x'(d) = x(d) + N(0,1) × βL(d);
          Update X* with x'.
         endif
         Replace x with x'.
        else
          Decrease x.h by one;
          if x.h==0
            /*refract x to a new x'*/
    for each stag
      Calculate the distance between the stag and all hinds and select the nearest hind.
      new = (stag+hind)/2;
      Mate stag with the selected hind.
    end for
    Select the next generation with roulette wheel selection.
    Update the Pareto optimal solutions.
    t=t+1
end while
Consider the best front and evaluate the solutions by assessment metrics.
```

Fig. 3. The pseudo-code of a multi-objective H-WG.

```
Set the parameters.
Initialize a random population P of n waves.
Form the initial Pareto optimal fronts.
Select a type of mutation according to Fig. S.3.2 from Supplementary material S.3.
X*=the best solution.
while (t< maximum number of iteration)
    for each x ∈ P
        /*propagate x to a new x'*/
        Generate a neighbor of x named as x'.
        if f(x') is better than f(x)
         if f(x') is better than f(X*)
            /*break x'*/
            Consider a memory to save this point as a good solution.
            Make a neighbor from this solution and update x.
            Update X* with list of memory.
         endif
         Replace x with x'.
        else
            Decrease x.h by one;
            if x.h==0
              /*refract x to a new x'*/
              x'(d) = N((X*(d)+x(d))/2, |X*(d)-x(d)|/2);
              γ' = γ × f(x)/f(x');
            endif
        endif
    endfor
    /*update the wavelengths*/
    γ = γ ×α^(-((f(x)-fmin+ε)/(fmax-fmin+ε)))
    t=t+1;
endwhile
return X*
Select the best optimal front and consider the evaluation metrics.
```

Fig. 4. The pseudo-code of a multi-objective H-WT.

maximum desired numbers ($MAX^{\square}$) of each level is estimated by a half of number of nodes for in such levels *i.e.* manufacturers, distributers, collectors and recyclers. The fixed cost and capacity of opening facilities in test problems are benchmarked from Devika et al. (2014) and the details are reported in Supplementary material S.8.

Taguchi method has been conducted to find out the best parameters used in our algorithms for solving each test problem. Taguchi (1986) method considers a group of factors based on orthogonal arrays and classified them into two main groups *i.e.* control and noise factors. While the effect of the controllable factor should be maximized, the effect of the noise factors must be minimized. The method calculates the value of response variation based on signal and noise ratio (Golshahi-Roudbaneh et al., 2017). The details of the Taguchi method utilized for tuning the parameters of the proposed hybrid algorithms and the levels and factors of them are presented in Supplementary material S.9. As a result, Table 4 gives the best setting for the main parameters of the proposed hybrid algorithms in this study. In addition, the effect plot of Signal to Noise (*S/N*) ratio for the proposed hybrid metaheuristic algorithms with priority-based (pri) representation and also transportation (tra) matrix representation are shown in Supplementary material S.9.

The developed sustainable closed-loop tire SCND problem has three conflicting objective functions. Hence, the trade-off between the objective functions leads to find a set of optimal solution called Pareto solution (Govindan et al., 2014). To compare the quality of the Pareto solutions of the proposed hybrid metaheuristics algorithms, four assessment metrics were explored from the literature including Number of Pareto Solution (NPS), Mean Ideal Distance (MID), Maximum Spread (MS), and Spread of Non-dominance Solution (SNS) (for more details see Supplementary material S10). All algorithms are coded in C++ and built in Microsoft Visual Studio 2014. All results were obtained on a Laptop with processor Core 2 Duo-2.26 GHz and 2 GB of RAM.

5.1. Evaluation of the constitutive algorithms

To find efficient hybrid metaheuristic algorithms, the advantages and disadvantages of the main algorithms are evaluated for sustainable closed-loop tire SCND problem. In this order, the main algorithms (i.e. WWO, RDA, GA, TA, and SA) were used to solve the test problems. The results have been reported in Supplementary material S11. According to the obtained results, the advantages

```
Initialize the Red Deers population.
Calculate the fitness and sort them and form the hinds (N_hind) and male RDs (N_male).
Form the initial Pareto optimal fronts.
while (t< maximum number of iteration)
   for each male RD
      /*propagate x to a new x'*/
      x'(d) = x(d) + U(−1,1) × γL(d) ;
      if f(x') is better than f(x)
         The new male RD is replaced with the current one.
      endif
   end for
   Form harems: (V_n = v_n − max_i{v_i}; P_n = |V_n / Σ_{i=1}^{N_Com} V_i|; N.harem_n = round{P_n.N_hind}).
   for each male
      Mate male commander with the selected hinds of his harem randomly.
      new = (com+hind)/2;
      Select a harem randomly and name it k.
      Mate male commander with some of the selected hinds of the harem.
   end for
   Select the next generation with roulette wheel selection.
   Update the Pareto optimal solutions.
   t=t+1;
end while
Select the best optimal front and consider the evaluation metrics.
```

Fig. 5. The pseudo-code of a multi-objective H-RW.

Table 2
The level, number and size of test problems.

Problem levels	Test problem	Size (I, M, J, L, N, R, T, C, P)
Small	P1	(13, 16, 21, 20, 15, 13, 2, 2, 12)
	P2	(15, 29, 30, 31, 19, 18, 3, 2, 12)
	P3	(17, 30, 32, 32, 21, 19, 3, 2, 12)
Medium	P4	(25, 39, 38, 41, 29, 24, 4, 4, 12)
	P5	(29, 42, 40, 44, 32, 26, 5, 4, 12)
	P6	(32, 44, 42, 46, 32, 26, 5, 4, 12)
Large	P7	(47, 65, 69, 131, 43, 36, 6, 6, 12)
	P8	(50, 69, 73, 136, 46, 38, 7, 6, 12)
	P9	(54, 72, 76, 140, 49, 40, 8, 6, 12)

Table 3
The parameters and their surfaces for random test problems.

Parameters	Surfaces
PC_i^I	$rand\{3, 4\}$
PC_r^R	$rand\{1, 2\}$
PC_{mp}^M, PC_{jp}^J , PC_{np}^N	$rand\{5, 6, ..., 10\}$
MC_{mpt}^M, MC_{jp}^J, MC_{np}^N, MC_{rc}^R	$rand\{2, 3, ..., 5\}$
$TC_{\square}^{\square}$	$rand\{1, 2, ..., 6\}$
$EH_{\square}^{\square}$	$\sim U(0.2, 2)$
$EO_{mt}^M, EO_j^J, EO_n^N, EO_{rc}^R$	$rand\{1, 2, ..., 10\}$
$EM_{mpt}^M, EM_{jp}^J, EM_{np}^N, EM_{rc}^R$	$rand\{6, 7, ..., 9\}$
ED_p	$rand\{5, 6, ..., 15\}$
d_{lp}	$rand\{16, 17, ...24\}$
a_{lp}	$\sim U(0.2, 0.6)$
$FJ_{mt}^M, FJ_j^J, FJ_r^R, FJ_{nc}^N$	$rand\{5, 6, ..., 10\}$
$VJ_{mt}^M, VJ_j^J, VJ_n^N, VJ_{rc}^R$	$rand\{2, 3, ..., 6\}$
$VL_{mpt}^M, VL_{jp}^J, VL_{np}^N, VL_{rc}^R$	$\sim U(0.1, 1)$
$FL_{mt}^M, FL_j^J, FL_{rc}^R, FL_n^N$	$rand\{10, 20, ..., 1000\}$
B_{pt}, U_c	$\sim U(0, 0.2)$

and disadvantages of each main metaheuristic algorithm are outlined as follows:

- Red Deer Algorithm (RDA): As mentioned in Supplementary material S1, RDA inspired by Red Deer's (RD) mating divides the initial population in two types i.e. male RDs and hinds. This algorithm considers three search operators to make an interaction between the phases. Roaring the males does the local search for the best solutions (Samadi et al., 2018). Fighting between two types of males i.e. commanders and stages informs the exploitation properties. Finally, mating behavior performs the exploration phase in three ways to find new potential areas (Hajiaghaei-Keshteli and Fathollahi Fard, 2018). According to the results stated in Supplementary material S11, RDA has more computational time to achieve the best solutions. Furthermore, in most of the evaluation metrics except in MID shows an efficient behavior.
- Water Wave Optimization (WWO): WWO considers the water wave shallow models and simulates three operators for water waves to find the optimal solutions. Propagation operator by propagate the water randomly enhances the exploration

Table 4
Tuned parameters of algorithms.

Algorithm	Tuned Parameters
H-RS^{pri}	MaxIt = 200; nPop = 200; N_{male} = 15; c = 0.8; SubIt = 40; R_t = 0.9; T0 = 1500; T_M = Insertion;
H-RS^{tra}	MaxIt = 200; nPop = 150; N_{male} = 15; c = 0.8; SubIt = 40; $R_\propto$ = 0.9; T0 = 2000; T_M = Insertion;
H-WG^{pri}	MaxIt = 600; nPop = 250; a = 1.01; b = 0.1; h_{max} = 6; T_C = Double-point;
H-WG^{tra}	MaxIt = 600; nPop = 250; a = 1.001; b = 0.1; h_{max} = 6; T_C = Double-point;
H-WT^{pri}	MaxIt = 600; nPop = 200; h_{max} = 6; T_M = Reversion; TL = 40;
H-WT^{tra}	MaxIt = 600; nPop = 200; h_{max} = 6; T_M = Swap; TL = 40;
H-RW^{pri}	MaxIt = 600; nPop = 250; N_{male} = 30; a = 1.1;
H-RW^{tra}	MaxIt = 600; nPop = 250; N_{male} = 30; a = 1.1;

properties. While breaking operator aims to increase the exploitation phase. Finally, refraction operator by using a probabilistic rule helps the algorithm to escape from local optima (Fard and Hajiaghaei-Keshteli, 2018). WWO has also some advantages and disadvantages. According to the results of the test problems (see Supplementary material S11), WWO has more computational time to search solution space rather than other ones (expected RDA). In addition, WWO for MID and SNS shows a good behavior. Although according to NPS metric, GA and RDA are better than WWO, in the term of MS metric, WWO was in the second rank after RDA.

- Genetic Algorithm (GA): GA utilizes a set of population and modifies them by two operators i.e. crossover and mutation (which are blind in search space). According to the results summarized in Supplementary material S11, although in small sizes GA has lower computational time, by increasing the size of problems, the computational time is similar to the WWO and RDA. In addition, GA results only for NPS metric obtained an acceptable value (after RDA). Besides, in the other evaluation metrics, GA has not reached proper results rather than other ones (Wang et al., 2016).
- Simulated Annealing (SA): SA as a well-known single-solution technique by a probabilistic accepting rule for the new solutions controls an interaction between the intensification and diversification phases. According to Supplementary material S11, SA in the all test problems (small, medium, and large sizes) has the lowest computational time. However, in this problem SA algorithm cannot obtain comparative results according to none of assessment metrics (Govindan et al., 2014).
- Tabu Search (TS): Another well-known single-solution metaheuristic is TS. Using an adoptive memory with a set of solutions as the Tabu list gives this chance to make a balance between the phases (Govindan et al., 2015a,b). According to the results (Supplementary material S11), TS has more computational time rather than SA. But, based on the evaluation metrics, the performance of the both algorithms were same.

According to the results of each individual metaheuristic algorithm, we find the main advantages and disadvantages of them for solving sustainable closed-loop tire SCND problem. The proposed hybrid metaheuristic algorithms are developed by considering the capability of the individual ones to solve the underlying problem. The main reasons for hybridizing the individual metaheuristic algorithms for achieving better results could be highlighted as follow:

- H-RS algorithm aims to decrease the computational time of the RDA. As reported in Supplementary material S11, SA has the lowest computational time to reach the Pareto set for the underlying problem. In this regard, instead of roaring process, SA is utilized to reduce the computational time. Furthermore, as mentioned in RDA, roaring does a local search. While the two other operators perform the exploration and exploitation separately. So, considering SA as a sub-loop by proposing both search phases inside itself can be more helpful for RDA to improve the search mechanism intelligently. In this way, we make better interaction between the phases of the RDA.
- H-WG algorithm uses the crossover operator of the GA to enhance the exploration properties (since GA was comparative with other ones according to NPS metric), and reduce the computational time of the WWO.
- H-WT is developed to reduce the computational time and improve the MS and SNS assessment metrics. We apply the adoptive memory of TS algorithm as the main advantage of the TS algorithm for solving the underlying problem (Supplementary material S11). In this regards, the exploitation property of the WWO algorithm is promoted for developing H-WT algorithm. As result the computational time and quality of solutions (according to the MS and SNS assessment metrics) would be improved in H-WT rather than WWO algorithm.
- H-RW consists of the RDA and WWO. The results of the RDA and WWO algorithms were more comparable rather than other individual algorithms based on the assessment metrics (Supplementary material S11). The exploitation and exploration phases of the H-RW are developed considering WWO and RDA algorithms, respectively. Since NPS and MS metrics are depending on diversification phase, we used RDA for exploration (as summarized in Supplementary material S11 the NPS and MS metrics of the RDA is better than other individual algorithms).

5.2. Evaluation with standard benchmarked functions

To evaluate the performance of the proposed hybrid metaheuristic algorithms (Ding et al., 2017), twelve standard benchmarked functions were selected from Ghorbani and Babaei (2014). Results were compared with other metaheuristic algorithms including Gravitational Search Algorithm (GSA), Particle Swarm Optimization (PSO) and Real Coded Genetic Algorithm (RCGA) that presented by Ghorbani and Babaei (2014). In addition, a recent multi-objectives hybrid algorithm namely HEV proposed by Govindan et al. (2015a,b) is used to evaluate the performance of the proposed hybrid metaheuristic algorithms. HEV hybridizes electromagnetism-like algorithm and variable neighborhood search. To solve the standard benchmarked functions, the single objective form of the HEV algorithm is coded. The details of the benchmarked test problems are given in Supplementary material S12. It should be mentioned, all used standard benchmarked functions were also adopted from CEC 2010 (Mallipeddi and Suganthan, 2010). Since the benchmarked problems have single objective function, the proposed hybrid metaheuristic algorithms are modified to the standard single objective ones. The parameters of the proposed hybrid algorithms are tuned according to the twelve benchmarked problems by Taguchi method and reported in

Supplementary material S12. The hybrid algorithms are run for thirty times and mean computational time and the mean errors from the global solution (i.e. zero) are calculated and summarized in Tables 5 and 6. In addition, the convergence behavior of hybrid algorithms is illustrated by Figs. 6–9 for four benchmarked functions. Due to page limitation, the rest of convergence analyses are reported in Supplementary material S12.

As illustrated in Table 5, the average of the mean computational time among the benchmarked functions for RCGA algorithm is less than other ones. Nevertheless the averages of the mean computational time of the proposed hybrid algorithms are less than GSA algorithm and HEV hybrid algorithm and close to PSO algorithm. Furthermore the average of the mean computational time of the H-WG is less than PSO, GSA and HEV. In addition, as can be seen, HEV as another recent hybrid algorithm has more computational time in comparison of proposed hybrid metaheuristic algorithms for mean computational time. For *Quratic* and *Rosenbrok* function, the mean computational time of the proposed H-WG is less other algorithms. As shown in Figs. 6–9 and Fig. S.12.1-S.12.9 of the Supplementary material S12, the convergence behavior of the H-WG is better than other hybrid ones for the most functions including *Ackley*, *Rastrigin*, *Penalised 1*, *Quratic*, *Schwefel 1.2*, *Schwefel 2.2.1 Schwefel 2.2.2*, *Sphere*, and *Rosenbrok*. For the *Step*, *Penalised 2*, and *Greiwank* functions the H-RW shows the better convergence behavior rather than other hybrid algorithms (Figure S.12.1-S.12.3 of the Supplementary material S12).

As summarized in Table 6, it can be seen that although the computational time of the H-WG algorithm is more than RCGA algorithm slightly, the mean error of H-WG for the entire functions are less than RCGA. For the *Step* function, all proposed hybrid algorithms reach to the global solution. Results demonstrated that excepted *Penalised 1*and *Penalised 2* functions were HEV hybrid algorithm has less mean error, in other functions the proposed hybrid algorithms have less mean error.

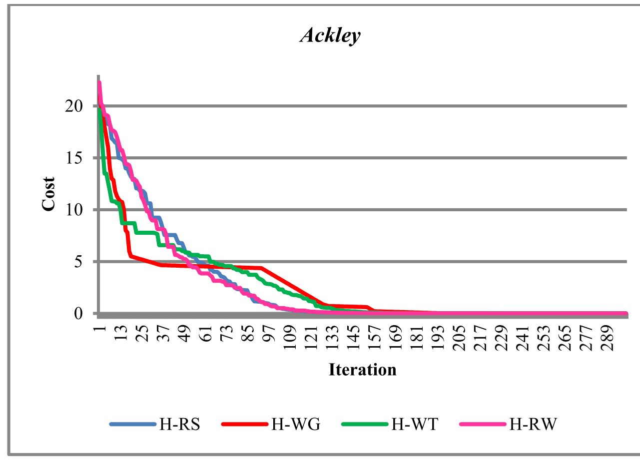

Fig. 6. The convergence behavior of hybrid algorithms for *Ackley*.

5.3. Validation with epsilon constraint method

To validate the hybrid metaheuristic algorithms in a small size, an Epsilon Constraint method (EC) is utilized. This method firstly proposed by Haimes et al. (1971) is used for multi-objective

Table 5
The mean computational time (Second).

Benchmarked problem	Ghorbani and Babaei, 2014			Govindan et al. (2015a,b)	Proposed hybrid metaheuristic algorithms			
	GSA	PSO	RCGA	HEV	H-RS	H-WG	H-WT	H-RW
Ackley	91.12	41.6	28.91	76.54	50.64	33.14	41.86	38.65
Griewank	92.91	40.78	28.09	75.39	48.19	34.63	42.08	37.26
Penalised1	105.54	56.71	39.58	79.63	64.82	52.31	56.89	51.66
Penalised2	104.35	43.06	36.48	78.21	62.89	51.65	45.83	39.71
Quratic	91.45	38.48	27.99	74.25	48.76	26.97	44.18	37.25
Rastrigin	90.98	37.89	28.45	71.68	46.51	31.93	45.12	49.78
Rosenbrok	98.30	42.91	40.11	74.18	54.27	40.03	53.18	57.48
Schwefel 1.2	95.77	38.86	27.86	75.57	48.94	35.28	47.41	50.63
Schwefel 2.21	90.51	42.18	28.35	78.92	49.21	36.15	43.28	47.19
Schwefel 2.22	90.08	40.74	27.41	76.54	46.27	33.19	40.82	38.15
Sphere	90.09	37.59	28.68	77.17	45.83	34.61	39.25	35.06
Step	90.21	36.96	26.51	73.89	47.21	35.75	29.18	38.92
Average time	94.27	41.48	30.7	75.99	51.1283	37.53	44.09	43.4783

Table 6
The comparison of mean errors resulted from different algorithms.

Functions	Ghorbani and Babaei, 2014			Govindan et al. (2015a,b)	This study			
	GSA	PSO	RCGA	HEV	H-RS	H-WG	H-WT	H-RW
Ackley	1.1E-05	2E-02	2.15	1.57E-02	1.54E-07	**0**	6.23E-05	3.45E-02
Griewank	2.9E-01	5.5E-02	1.16	6.57E-07	**8.29E-10**	7.68E-09	2.86E-02	3.67E-04
Penalised 1	4.2E-13	2.6E+02	5.3E-02	**2.87E-15**	2.87E-03	8.14E-02	1.2434	2.85E-01
Penalised 2	3.2E-32	7.1E+02	8.1E-02	**0**	6.89E-08	7.45E-05	3.92E-09	4.12E-10
Quratic	5.33E-01	1.04	5.6E-01	0.34	0.1854	1.78E-01	**3.76E-03**	5.37E-02
Rastrigin	15.32	72.8	5.92	5.78	3.78	**0**	6.89	8.15
Rosenbrok	25.16	1.7E+03	1.1E+03	23.86	22.65	18.54	6.54E+01	**12.3**
Schwefel 1.2	1.6E+03	2.9E+03	5.6E+03	3.62E-03	5.18E-07	**3.82E-14**	2.97E-4	2.17E-05
Schwefel 2.21	8.5E-06	23.6	11.78	2.57E-05	1.36E-05	5.12E-03	4.27E-01	**1.26E-07**
Schwefel 2.22	6.09E-05	2	1.07	6.38E-11	**6.27E-19**	1.43E-04	9.52E-05	2.67E-09
Sphere	2.1E-10	5E-02	23.45	3.29	**4.37E-19**	2.17E-16	7.15E-14	6.74E-08
Step	2.1E-10	2E-02	24.52	3.87E-28	**0**	**0**	**0**	**0**
Summation of errors	1641.3	5669.58	6770.74	3.33E+01	2.66E+01	**1.88E + 01**	7.40E+01	2.08E+01

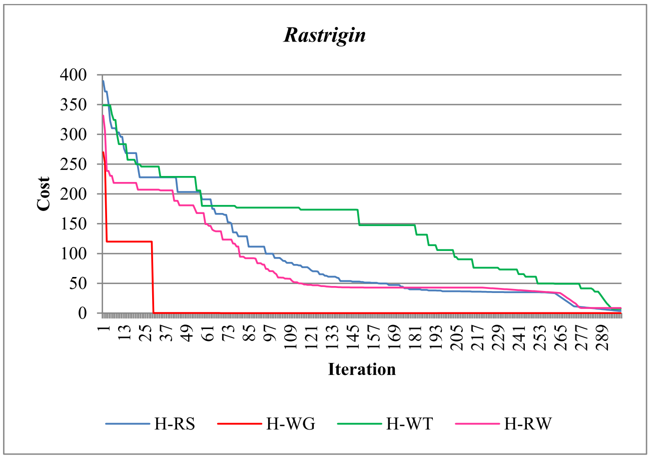

Fig. 7. The convergence behavior of hybrid algorithms for *Rastrigin*.

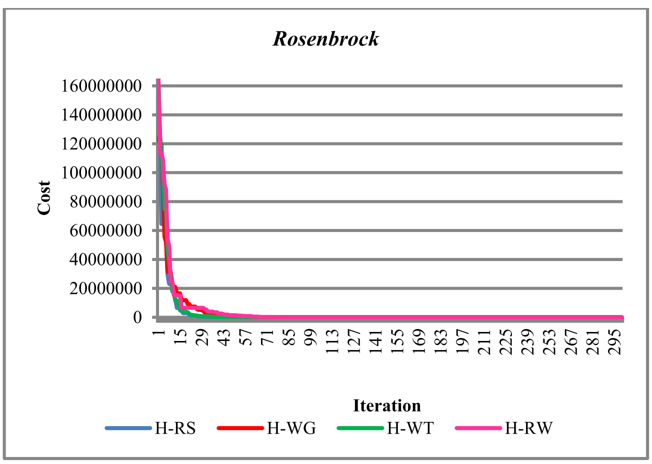

Fig. 8. The convergence behavior of hybrid algorithms for *Rosenbrok*.

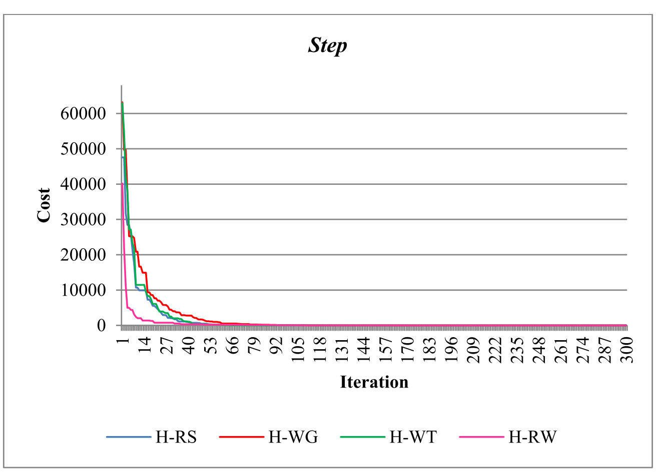

Fig. 9. The convergence behavior of hybrid algorithms for *Step*.

optimization problem. In this way, the structure of methodology is formulated by only one objective i.e. the main objective function to be optimized and the other objectives as the constraints by allowable bounds (Fard et al., 2017). In this exact method, Pareto solutions are generated by modifying the bounds of objectives (Sahebjamnia et al., 2018). According to our developed model, following equation states the used EC method as follows:

$$\begin{array}{l} \min Z_1 \\ s.t. \\ Eq.(4)-(34) \\ \quad Z_2 \leq \varepsilon_1 \\ \quad Z_3 \geq \varepsilon_2 \\ \quad Z_2^{min} \leq \varepsilon_1 \leq Z_2^{max} \\ \quad Z_3^{min} \leq \varepsilon_2 \leq Z_3^{max} \end{array} \tag{35}$$

According to this approach, the optimum value for the main objective function (Z_1) is reached. Also, to find the positive ideal solution and negative ideal one for the other objectives (Z_2^{min}, Z_3^{max}), the main objective should be changed. Furthermore, the optimum bounds for the two other objective functions (ε_1, ε_2) of the developed model are found by using the average of positive and negative idea solutions.

In addition, four proposed hybrid metaheuristic algorithms in two versions of solution representations are also employed to solve the test problems. Based on the results of Supplementary material S13 and other comparison of hybrid metaheuristics mostly reported in Supplementary material S11, it is evident that the transportation matrix representation is strongly better than priority-based one. Hence, the outputs of transportation matrix's solutions of algorithms are considered in this sub-section by Tables 7 and 8. Besides, the results of priority-based representation of algorithms are provided in Supplementary material S13. To make easier the comparison, it is tried to sort the solutions of algorithms as seen in Table 7. According to the Pareto frontier of EC, the non-dominated solutions of each hybrid metaheuristic algorithm are modified. These non-dominated solutions have been highlighted by Table 7. For instance, the solutions of exact method dominate the solution 5 and 6 for H-WG hybrid algorithm. To check the performance of Pareto frontier of algorithms in all test problems, the modified number of Pareto solution (MNPS) and its successful percentage i.e. $\frac{MNPS}{NPS}$ are computed and its results are provided in Table 8. It is clear that the higher value of MNPS brings the better quality of algorithm. The average of percentage of modified non-dominated solutions for H-RS, H-WG, H-WT and H-RW are 0.4, 0.59, 0.37 and 0.41, respectively. Therefore, H-WG has an acceptable rate of Pareto frontier in comparison of other hybrid metaheuristics. By another point of view, however, the time of completing of eight Pareto solutions for EC method in test problem P1 is 1208 s by using GAMS software, the maximum time among whole hybrid algorithms is reported as 27 s. In this regard, by increasing the size of problem, the computational time for EC method increases exponentially. So, for large sizes i.e. P7, P8 and P9, the results of exact methods are not available to compare with hybrid metaheuristics. In this way, the next sub-section presents this comparison especially for large-scale network by using four assessment metrics of Pareto optimal sets.

5.4. Computational results

To evaluate the performance of the proposed hybrid metaheuristic algorithms, each test problem is solved for thirty times. The results of each test problem are summarized for the average of the ten random generated test problems and solved thirty times (totally$90 \times 30 = 2700$run is done). Due to the multi-objective features of the proposed model and algorithms, four assessment metrics including NPS, MID, MS, and SNS are considered. In addition, the computational time of the algorithms is reported to evaluate the proposed hybrid algorithms.

Fig. 10 shows the computational time of the proposed hybrid

Table 7
Pareto solutions of algorithms for test problem P1.

Number	EC			H-RS			H-WG			H-WT			H-RW		
	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3
1	**10001**	10588	2509	**10253**	10412	2579	**10146**	10498	2616	**10819**	**9377**	2418	**10067**	**9077**	2455
2	10322	10382	2552	10710	9063	2590	10310	9383	2618	11128	10039	2428	11615	9304	2470
3	10664	10176	2595	10836	9554	2606	10395	10447	2646	11248	9745	2446	12018	10169	2483
4	11032	9971	2638	11786	9092	2619	10606	9362	2647	11440	10880	2455	12151	10317	2496
5	11432	9765	2681	11913	**9194**	2635	11415	10666	2712	12659	10106	2470	12237	10166	2532
6	11874	9559	2725	12919	10647	2661	11931	9565	2722	13061	11113	2491	12655	9812	2573
7	12376	9354	2768	12920	10390	2672	12170	**9273**	2762	14055	9582	2491	12662	9985	2691
8	12970	**9148**	**2811**	13019	9634	2675	12318	9377	2776	14233	9754	2533	13877	9533	2751
9	–	–	-	13296	10901	2696	13139	10071	2815	14269	9505	2553	14381	10341	2838
10	–	–	–	13359	9068	2712	13743	9799	**2830**	14449	9485	2558	14392	9340	2880
11	–	–	–	13507	9877	2714	–	–	–	14636	11026	2695	14569	10236	**2885**
12	–	–	–	13752	9763	2720	–	–	–	14840	10417	2737	–	–	–
13	–	–	–	14038	10531	2728	–	–	–	14984	10355	**2825**	–	–	–
14	–	–	–	14117	10591	2739	–	–	–	–	–	–	–	–	–
15	–	–	–	14226	9373	**2790**	–	–	–	–	–	–	–	–	–

Table 8
Comparison of hybrid metaheuristics with exact method by modified number of non-dominated solutions and its percentage among total number of Pareto frontier.

Test problem	H-RS		H-WG		H-WT		H-RW	
	MNPS	MNPS/NPS	MNPS	MNPS/NPS	MNPS	MNPS/NPS	MNPS	MNPS/NPS
P1	5	0.33	8	0.8	3	0.24	5	0.45
P2	4	0.4	7	0.7	4	0.3	5	0.41
P3	5	0.31	7	0.53	4	0.36	5	0.41
P4	6	0.54	6	0.42	5	0.55	6	0.4
P5	5	0.5	8	0.53	4	0.4	5	0.38
P6	4	0.36	6	0.6	5	0.35	6	0.4
Average		0.4		**0.59**		0.37		0.41

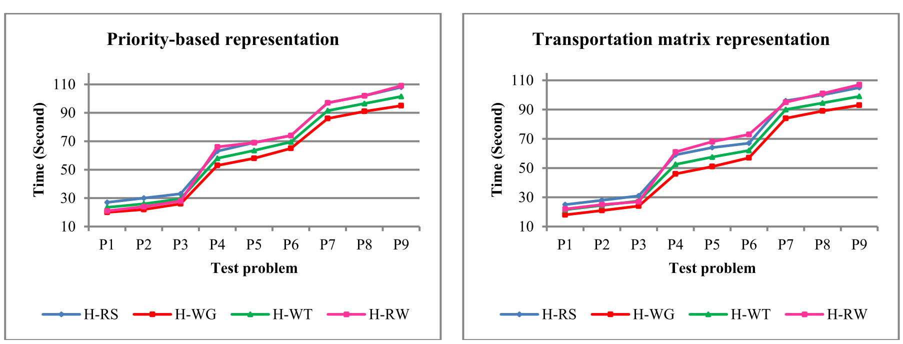

Fig. 10. The computational time of the proposed hybrid metaheuristic algorithms.

algorithms under two representation methods. Comparing the computational time based on the representation methods show that transportation matrix representation has shorter computational time than priority-based representation. The computational time of the H-WG is less than other developed hybrid metaheuristic algorithms in all sizes. Although the computational time of the H-RW algorithm is less than H-RS for small size test problems (*i.e.* P1–P3), it was increased considerably for medium and large size test problems (*i.e.* P4–P9). Among the proposed hybrid algorithm, the H-WT algorithm always has less computational time than the mean time of the all hybrid algorithms under the small, medium, and large size test problems. While the average computational time of the all individual algorithm for small and medium size test problems (i.e. 22.12 and 50.33 s) is less than the computational time of the H-WG (*i.e.* 21 and 51.34 s), for the large size test problems the computational time of the H-WG (88.67 s) is less than the average computational time of the all individual algorithm (i.e. 95.74 s). Our results show that computational time of the SA algorithm is less than all other hybrid and individual metaheuristic algorithms (Supplementary material S11).

Moreover, the non-dominated solutions for algorithms in a selected test problem *i.e.* P5 are set in Fig. 11. For each representation method, the outputs of algorithms are depicted separately. According to this figure, in priority-based representation method, H-WG and H-RS are mostly overcome to other approaches. In addition, for transportation matrix representation method, H-WG is strongly overcome to the others. It should be noted, in order to be faired, the number of Pareto optimal solutions equals to 5 for all methods in both representation methodologies.

We compare the efficiency of the proposed hybrid metaheuristic algorithms using the assessment metrics (i.e. NPS, MID, MS, and SNS) as comparison metrics. Hence the assessment metrics are

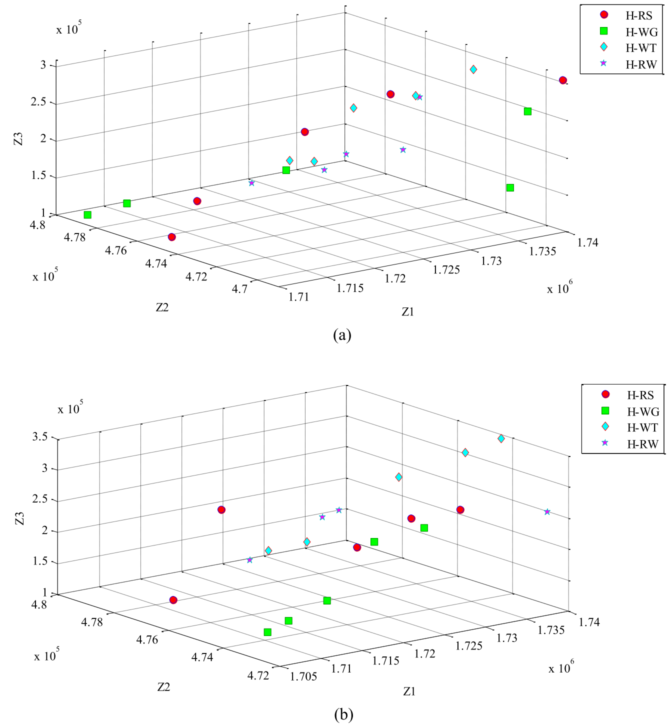

Fig. 11. The non-dominated solutions for the algorithms according to the two representation methods (*i.e.* (a) for *pri* and (b) for *tra*).

obtained according to the Pareto set for the proposed hybrid algorithms under each test problem and reported in Tables 9–12.

To evaluate the performance of the proposed hybrid meta-heuristics algorithms, the difference of the algorithms' assessment metrics are compared with Analysis of Variance (ANOVA). It has been used to determine whether there are any statistically significant differences between the Relative Percentage Deviation (RPD) of the algorithms. The RPD measure is formulated as follow:

$$RPD = \frac{|Alg_{sol} - Best_{sol}|}{Best_{sol}} \tag{36}$$

where Alg_{sol} is the output of algorithm and $Best_{sol}$ is the best value ever found in size of problem (Ruiz and Stützle, 2007). The means plot and least significant difference (LSD) intervals for the proposed hybrid algorithms and individual ones shown in Fig. 12. Since the computational time of the transportation representation is less than priority based representation, we show the means plot for transportation matrix representation. In addition, the results of priority based representation for hybrid metaheuristic algorithms

Table 9
NPS's computational results for algorithms.

Test problem	H-RS		H-WG		H-WT		H-RW	
	pri	tra	pri	tra	pri	tra	pri	tra
P1	14	15	14	10	11	13	15	11
P2	16	10	13	10	9	13	11	12
P3	16	16	13	13	13	11	13	12
P4	13	11	15	14	10	9	11	15
P5	10	10	11	15	12	10	15	13
P6	10	11	14	10	9	14	11	15
P7	11	13	14	13	12	9	14	11
P8	15	12	12	12	10	13	15	12
P9	11	11	13	10	12	12	15	11

Table 10
MID's computational results for algorithms.

Test problem	H-RS		H-WG		H-WT		H-RW	
	pri	tra	pri	tra	pri	tra	pri	tra
P1	2.706	1.754	1.656	1.136	1.078	1.399	1.409	2.869
P2	1.412	3.071	1.38	2.409	2.442	1.259	1.175	3.579
P3	1.88	3.594	2.552	1.546	2.106	3.8	2.92	2.542
P4	1.706	1.316	1.205	4.614	1.961	1.431	2.325	2.144
P5	3.53	2.193	1.104	1.204	3.004	4.91	3.688	1.853
P6	2.675	2.217	1.175	2.409	2.774	2.181	3.328	3.622
P7	1.412	2.632	1.104	3.341	3.817	1.263	4.246	3.352
P8	4.236	2.466	1.381	3.136	3.868	3.145	5.344	3.513
P9	1.706	3.071	2.828	2.273	4.084	3.136	6.720	4.401

are shown in Fig. S.11.7 from Supplementary material S11.

Based on the NPS metric, although there is no significant difference between hybrid algorithms, the performance of hybrid algorithms is better than the individual one. Among the hybrid algorithms, the performance of the H-RW is better than other ones. In addition, the TS and SA algorithms achieved the best computational times show poor performance in NPS metric (Fig. 12a). Fig. 12 b demonstrated that the H-WG is more effective than other algorithm in terms of the MID metric. However, there is no significant difference between the H-WG, H-RS, and H-WT algorithms. Similar to the NPS metric, TS and SA algorithms do not yield acceptable results based on MID metric. Fig. 12 c illustrated that RDA algorithm is more effective than the proposed H-RS algorithm. While there is no significant difference between H-WG, H-WT, and H-RW algorithms, they are more effective than RDA algorithm based on the MS metric. Although to the mean RPD of the SNS metric, there is no significant difference between H-WT, H-RW, and RDA algorithms, in terms of LSD of SNS metric the H-WT and H-RW are more effective than RDA algorithm (Fig. 12d).

5.5. Sustainability dimensions analysis

To validate the efficiency of our model, some sensitivity analyses have been done by changing the critical parameters of the developed model. In this regard, the test problem P5 is selected and solved by H-WG algorithm (the most efficient and effective hybrid algorithm). To analyze the sustainability dimensions, three parameters were investigated. We change the range of parameters to analyze the objective functions. The most important parameters for economic, environmental and social dimensions are the purchasing cost of the recycled tires from recycler (PC_r^R), environmental impact of released scraped tires on environment (ED_p), and effect of capacity of recycler (CAP_r^R). To specify the best solution among Pareto solutions, the crowding distance is considered to be minimized (Govindan et al., 2014).

5.5.1. Sensitivity analyses on the cost of purchasing the recycled tires

According to the main features of the closed-loop supply chain networks, a part of the final scraped tires would be back to chain. As given in Table 13, nine cases are considered and the objective functions are evaluated for each case. According to Fig. 13, by increasing the cost of purchasing the recycled tires, the total cost is mainly decreased. By increasing this parameter, amount of transformed recycled tires to manufacturing plant is increased. However, the third objective function has not changed much. It should be noted, the normalized values for the objectives are used in Fig. 13. Also, it can be seen the differences between the parameters are very impressive for the changes of objective functions. Moreover, results show that the price of the recycled tires on finished tire is very

Table 11
MS's computational results for algorithms.

Test problem	H-RS		H-WG		H-WT		H-RW	
	pri	tra	pri	tra	pri	tra	pri	tra
P1	314683	378213	389217	421648	332674	389210	442781	398574
P2	621096	704962	698535	729910	764832	731825	784503	756211
P3	652671	721905	773526	732891	754893	780329	821904	792852
P4	923619	976435	854733	932415	984672	953718	1023516	994673
P5	1367703	1425704	1526794	1550328	1689524	1590438	1734255	1631563
P6	1450329	1527365	1495503	1698437	1724491	1824437	1650439	1731805
P7	1138439	1032785	1054783	1230436	1197265	1091837	1128437	1178439
P8	943672	985713	915734	990425	932675	985246	932215	958437
P9	1459430	1624673	1738299	1752145	1790523	1824673	1732901	1685904

Table 12
SNS's computational results for algorithms.

Test problem	H-RS		H-WG		H-WT		H-RW	
	pri	tra	pri	tra	pri	tra	pri	tra
P1	390536	336137	421546	409327	457438	467433	389658	372891
P2	715324	726645	840923	751342	732657	709654	695034	784633
P3	1026743	1015849	1008426	1026859	1064529	1009438	1043720	1059483
P4	1168549	1132076	1184923	1126327	1198635	1215573	1148523	1204683
P5	1990645	2075842	2043671	2096815	2137658	2167965	2187436	2190654
P6	2489764	2256437	2687549	2453671	2557438	2516758	2490863	2538544
P7	2890754	3190654	3268543	3290754	3280645	3265701	3176854	3220549
P8	3754613	3829760	3850934	3921855	4109634	3986725	4062794	4014783
P9	5190645	5632781	5732897	5234186	5843904	5910657	5380729	5678439

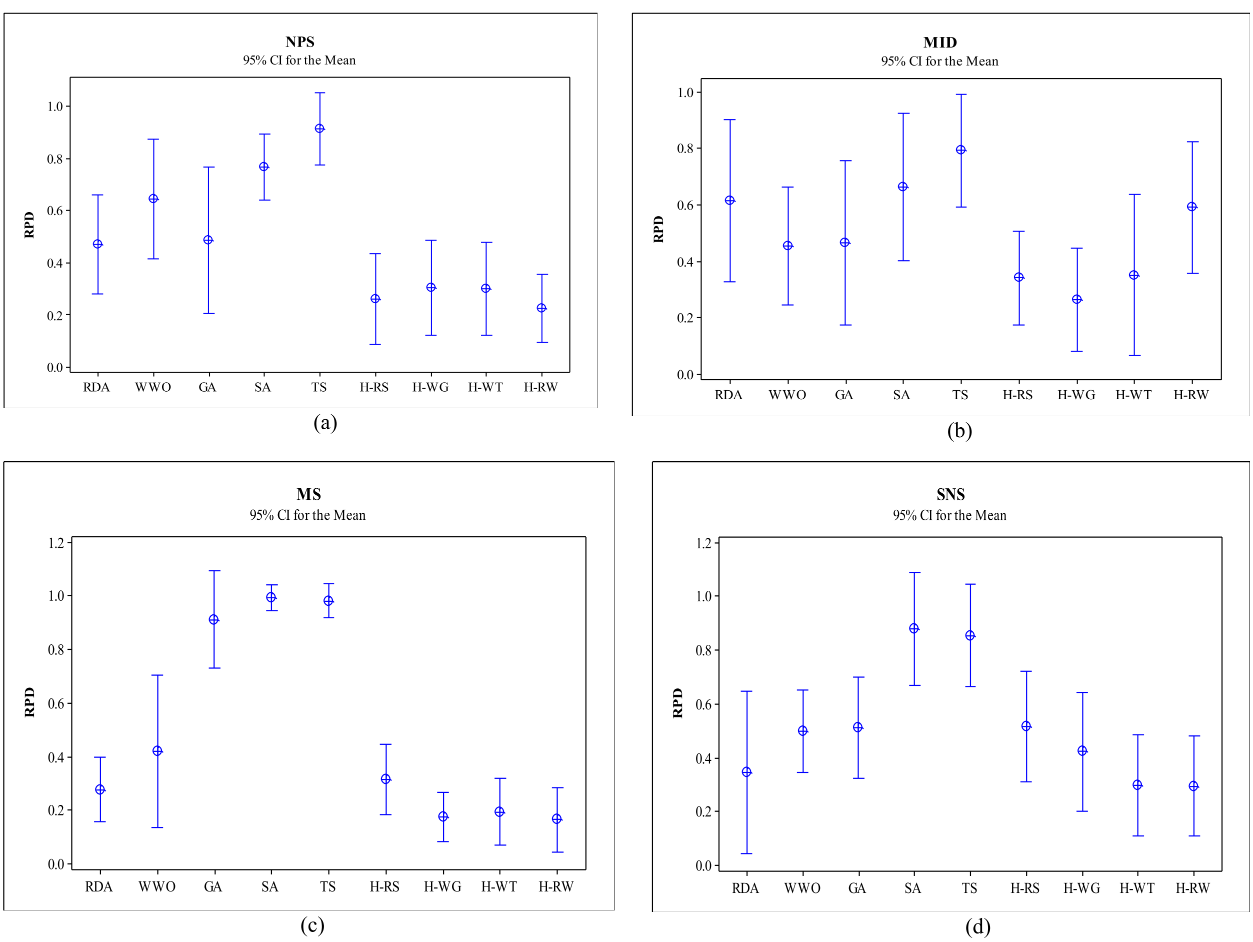

Fig. 12. ANOVA plots for the assessment metrics in term of RPD by considering transportation matrix representation (*i.e.* (a) for NPS, (b) for MID, (c) for MS and (d) for SNS).

Table 13
An analysis on the profits of returned tires on the network.

Number of cases	PC_r^R	Z_1	Z_2	Z_3
C1	1	1594372.6847	763922.5163	277892.6455
C2	2	1584266.7135	758249.1074	268352.7479
C3	3	1574321.8975	773128.3521	265329.5433
C4	4	1547152.5607	781389.9357	257850.7480
C5	5	1526689.0476	778439.2954	263289.4739
C6	6	1448932.5167	705832.5739	276382.1945
C7	7	1426854.9533	693871.5395	283372.1853
C8	8	1432789.5177	673822.8911	259317.3472
C9	9	1384256.5136	653318.5247	278314.9318

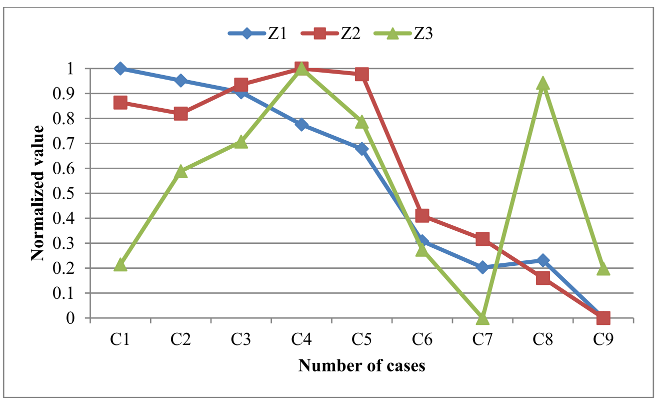

Fig. 13. The behavior of objective functions in term of sensitivity analyses of the purchasing cost of recycled tires.

effective. Indeed by changing the recycling cost, the first and second objective functions would be change considerably. Similarly Wang et al. (2016) revealed that recycling cost is very important for the price of tire produced. Therefore, supply chain managers have to control the recycling cost.

5.5.2. Sensitivity analyses on the environmental impacts of released scraped tires

In this part, the environmental effect on the released scraped tires (ED_p) by only considering one type of tire ($p = 1$), are designed in nine different cases by increasing the amount of this parameter. According to Table 14 and Fig. 14, an increasing for this penalty parameter leads to a decreasing for the total cost of economic considerations and increasing the social benefits in major cases. Since, the amount of recycled tires increases regarding to an increase in the value of released scraped tires. So, economic aspects will be decreased. Also, by increasing the amount of collected and recycled tires, the variable job opportunities would be increased. Moreover, it is obvious by increasing this parameter the amount of second objective function will be increased. Similarly, Fard and Hajiaghaei-Keshteli, 2018 indicated that environmental impacts can directly affect on the total cost. They have proven that an increase for the environmental effects may lead a decrease in the total cost of closed-loop supply chain.

Table 14
An analysis on the environmental effect of released scraped tires.

Number of cases	ED_p	Z_1	Z_2	Z_3
C1	5	1528215.5835	672470.0583	278392.4758
C2	10	1495194.6756	683591.5382	275451.6857
C3	15	1464911.5867	695509.6532	278152.5260
C4	20	1448932.5167	705832.5739	276382.1945
C5	25	1435744.6588	716952.8413	269393.1395
C6	30	1438155.3829	728073.6137	262882.0475
C7	35	1423317.5722	739193.5274	265476.6903
C8	40	1392895.3846	750314.4188	251863.8042
C9	45	1379466.3862	761434.7193	253925.5735

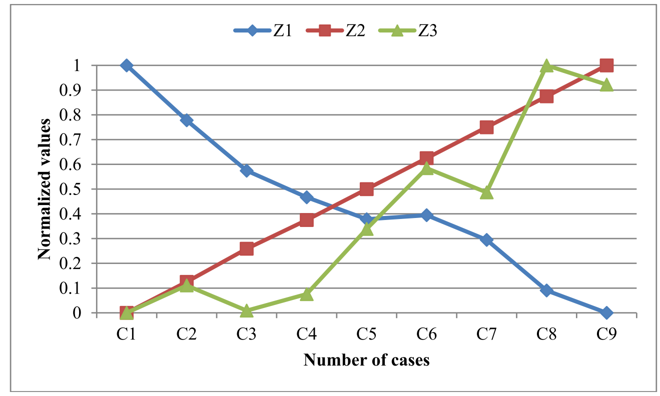

Fig. 14. The behavior of objective functions in term of sensitivity analyses of environmental effect of released scraped tires.

5.5.3. Sensitivity analyses on the capacity of recyclers for social benefits

Here, a set of analyses has been performed to assess the effect of capacity of recyclers on the social benefits. The social dimensions considered in this study are the number of created job opportunities and worker's lost days. The effect of the capacity of recyclers (CAP_r^R) on the social benefits is considered by a set of sensitivity analyses. Generally, it has been proven that this parameter can directly affect on the social dimensions. Accordingly, an increase in the capacity of recyclers leads generally to a decrease into the social benefits. This effect is different for the two social dimensions. Although the number of job opportunities may be increased by an increase in the capacity of facilities, the worker's lost days will be decreased. That's why the social dimension shows a reduction in the analyses. As can be seen from Fig. 15, the environmental impacts can generally increase. Similarly, regarding the first objective function, the economic aspects by increasing this parameter is increased in most of the cases. The outputs for nine different cases are given by Table 15. Regarding the literature, Soleimani et al. (2016) showed that the capacity of facilities can be affected on the whole of sustainability dimensions. To prove our results, they revealed that by increasing the capacity of facilities, not only the number of line workers will be grown

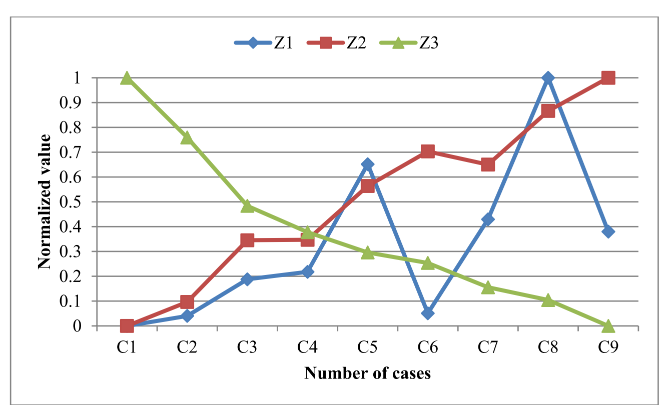

Fig. 15. The behavior of objective functions in term of sensitivity analyses of social benefits according to the capacity of recyclers.

Table 15
An analysis on the capacity of recyclers for social benefits.

Number of cases	CAP_r^R	Z_1	Z_2	Z_3
C1	300	1421533.6843	693829.3947	241276.8942
C2	400	1427422.9842	697182.4552	257632.9016
C3	500	1448932.5167	705832.5739	276382.1945
C4	600	1453328.9513	705894.3947	283572.1844
C5	700	1516637.2894	713432.4014	289152.7318
C6	800	1428953.2486	718272.4573	292013.5241
C7	900	1484189.3857	716434.5622	298685.1945
C8	1000	1567439.2482	723938.5833	302172.2472
C9	1100	1476933.1985	728591.4574	309263.4559

accordingly but also the economical and environmental impacts are seemingly increased.

According to the analyses, the importance of some parameters is cleared. As mentioned earlier, sustainability dimensions consist of economic, environmental and social factors. Indeed the trade-offs between dimensions are so significant for decision makers. In the term of economic considerations, the cost of the recycling process is effective in tire supply chain. The price of the recycled tires for manufacturer is directly affected on the behavior of manufacturer for choosing between the supplier or recycler (Wang et al., 2016; Soleimani et al., 2016). Furthermore, it directly effects on the benefits of reverse network and also the impacts of environmental objective. Therefore, to control the flow of the sustainable tire closed-loop supply chain, the decision makers should control the recycling cost. Also, for the environmental impact for released scraped tires, it seems that managers should be focused more on this penalty parameter to reduce the environmental and economic aspects by collecting a higher percentage of scraped tires. Besides, for the social benefits, the capacity of facilities is directly affected on the number of workers and work's lost days for the companies. In this regard, the final decision maker needs to identify the preferences about the sustainability dimensions. Perhaps, the total cost is intended primarily. In a nutshell, the main suggestions for managerial insights can be outlined as follows:

- The used constraints in our developed model such as capacity constraints are more likely to be efficient in a real world. In this way, adopted decisions by managers should consider an interaction for social aspects and other sustainability dimensions (Govindan and Soleimani, 2017).
- The values of environmental effect for released scraped tires are important for the sustainability dimensions. So, estimating suitable values by using a proper database is helpful for adopted sustainable decisions as the managerial insights (Hajiaghaei-Keshteli and Fathollahi Fard, 2018).
- Executive constraints such as the prices of tires for each level are also significant. Also, according to the analyses, it can affect on the other parts of the model and its outputs. Therefore, controlling and setting a suitable decision for these parameters are so valuable for developed tire supply chain network (Amin et al., 2017).

6. Conclusion and future studies

This study for the first time in the literature developed the sustainable closed-loop tire supply chain network design model considering economic, environmental and social dimensions. The relevant literature has been reviewed and the main gaps were highlighted according to sustainability dimensions, model types, solution method, and the types of the products. While more scholars focus on economic dimension, less attention have been paid to environmental and social dimensions. Due to the computational complexity of the proposed problem, many scholars both proposed and developed metaheuristic algorithms to solve them. We evaluated the performance of the GA, SA, and TS as the traditional algorithms as well as RDA and WWO as the recent nature-inspired algorithms. By exploring the main advantages and disadvantages of the individual algorithms, four new hybrid metaheuristic algorithms were developed to solve large-scale problems. Four well-known assessment metrics of the Pareto optimal set and computational time were utilized to evaluate the effectiveness and efficiency of the proposed hybrid algorithms. Results demonstrated that although the computational time of the proposed algorithms were more than traditional ones insignificantly, there is significant difference between the proposed hybrid algorithm and individual ones according to the Pareto optimal set metrics.

To consider the generality of the proposed algorithm, twelve standard benchmarked functions were selected from the literature and solved. The results of the three well-known algorithms (*i.e.* RCGA, PSO, and GSA) have been compared with the results of the proposed hybrid algorithms based on the distance to global solution and convergence behavior. While there is no significant difference between the computational time of the proposed hybrid algorithm and RCGA, PSO, and GSA and also a recent developed hybrid algorithm namely HEV, the H-WG shown better performance rather than other algorithms based on the convergence behavior and distance to global solution. In addition, for the term of presented multi-objective model, the proposed four hybrid algorithms were validated by epsilon constraint method. In this regard, by considering the Pareto frontier of epsilon constraint method, the non-dominated solutions of hybrid algorithms are modified. The results show H-WG's solutions have the most acceptable rate of non-dominated solutions to overcome the solutions of exact solver.

Future researches could apply the proposed hybrid metaheuristic algorithms to solve the other large scale problems. Noteworthy, considering the extension of the global supply chain networks can increase the usefulness of the proposed hybrid algorithms to encounter with real cases. Furthermore, the scholars could modify the operators of the main individual recent algorithms i.e. RDA and WWO as well as four hybrid metaheuristic algorithms to increase the effectiveness and efficiency of them according to their problems. For instance in RDA, the mating process may be changed by adding some heuristic rules from variable neighborhood descent or the fighting process should be examined by considering tournament selection or roulette wheel to improve the interaction between phases. In addition, proposing more quantitative factors for sustainability dimensions *e.g.* consumer risk and value of local development can lead to better illustration of capability and applicability of the mathematical model in this context. Finally, the proposed network can be explored according to other applications of the scraped tire and recycled materials in the real case studies.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2018.05.245.

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