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Addressing a sustainable production-distribution supply chain network design problem considering carbon emissions policies by a hybrid whale optimization algorithm

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Abstract

Today's world has seen a further attention in the area of sustainability to integrate whole business networks in an efficient way. Regulations of carbon emissions and the sustainability dimensions enforce the decision-makers of supply chain networks to redesign their systems based on these factors. Such difficulties motivate us to develop a sustainable production-distribution supply chain network design problem considering carbon emissions policies among the first studies in this area. Accordingly, a mixed integer non-linear programming model has been developed. To tackle the proposed problem, its complexity increases exponentially while the size of problem increase. Hence, another innovation of this work is to introduce a new hybrid metaheuristic based on whale optimization algorithm as a recent successful optimizer to solve the complex and non-linear problems. The collaboration of applied algorithms has been designed by Taguchi method, satisfactorily. A comprehensive analysis has been evaluated through a comparative study along with some sensitivity analyses.

Keywords

Sustainability; production-distribution systems; supply chain network design; carbon emissions policy; hybrid metaheuristics; whale optimization algorithm.

1. Introduction

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The production-distribution systems have been investigated and analyzed in the recent years due to a rapid growth in sustainability attentions (Fard & Hajiaghaei-Keshteli, 2018). Sustainability should be considered in all of organizations due to recent governments' policies in the developed countries (Hajiaghaei-Keshteli & Fathollahi-Fard, 2018). Generally, the sustainability dimensions should be adjusted based on economic, environmental and social aspects for a production-distribution supply chain system (Absi, Dauzère-Pérès, Kedad-Sidhoum, Penz, & Rapine, 2013). Similarly, recent years have seen a rapid interest in environmentalism to consider the carbon emissions to design the supply chain network (Beamon, 1998; Benjaafar, Li, & Daskin, 2012; Ghosh, Jha, & Sarmah, 2016). In most of case studies, optimization of a supply chain (Kirkpatrick, Gelatt, & Vecchi, 1983) has been based on economic factors (profit maximization or cost minimization), with less or no regards to the negative impacts on the environment(Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2018b; Golmohamadi, Tavakkoli-Moghaddam,&Hajiaghaei-Keshteli, 2017; Sadeghi-Moghaddam, Hajiaghaei-Keshteli, & Mahmoodjanloo, 2019). By another point of view, recent protocols committed by international organizations and governments are mainly decided to control and to reduce carbon emission levels, more efficiently till 2020(Golmohamadi et al., 2017). Therefore, mitigating and reducing carbon emissions are one of main concerns in developing a sustainable supply chain network design (B. Zhang & Xu, 2013). This reason has been motivated to redesign of supply chain networks to incorporate goals from all dimensions of sustainability i.e. economic, environmental and social aspects (Absi et al., 2013; Fard & Hajiaghaei-Keshteli, 2018; Hajiaghaei-Keshteli & Fathollahi-Fard, 2018).

Overall, there are several options which have to be weighed, taking into consideration the numerous constraints and requirements (Bonney & Jaber, 2011). Most of developed decision-making models mainly focus on the location of facilities and the allocation between each level (Bouchery, Ghaffari, Jemai, & Dallery, 2012; Bouchery, Ghaffari, Jemai, & Tan, 2017). In this regard, there are a few works proposing the inventory decisions in addition to the sustainable dimensions (C.-L. Chen & Lee, 2004; X. Chen, Benjaafar, & Elomri, 2013; Darvish, Larrain, & Coelho, 2016; Daskin, Coullard, & Shen, 2002). Regarding the analytical based operations management adopted from the literature, the sources of green and environmental emissions should be eliminated and reduced from a robust production-distribution supply chain system. It is generally believed that assigning effective and efficient operations among design and management of supply chain networks, especially with carbon policies is a great challenge(Chan, Chung, & Wadhwa, 2005; Dobos, 2007; Hua, Cheng, & Wang, 2011). Therefore, reduction of emissions at each stage of the supply chain will induce an overall reduction in emissions (Jaber, Glock, & El Saadany, 2013). A sustainable supply chain emphasizes on being environmentally balanced while being economically viable (J. Li, Su, & Ma, 2017; Shu, Teo, & Shen, 2005). This includes strict carbon capping indicating some firms which should be regulated the main emissions of a sustainable production-distribution supply chain(Fathollahi-Fard & Hajiaghaei-Keshteli, 2018; Hajiaghaei-Keshteli & Fard, 2019). The main limitations are regularly to set the carbon taxing (Fathollahi-Fard, Hajiaghaei-Keshteli, & Mirjalili, 2018a), carbon capping and trading(Sahebjamnia, Fathollahi-Fard, & Hajiaghaei-Keshteli, 2018), and buying carbon credits from another firm (Fathollahi-Fard, Hajiaghaei-Keshteli, & Mirjalili, 2018b). All in all, this study employs all these three carbon policies to consolidate in a sustainable production-distribution and inventory control decisions model. Here, a brief review about two different but related streams of present work including production-distribution systems and carbon policies in supply chain networks have been overviewed.

1.1. Production-distribution supply chain network design

The general idea of supply chain networks is a facility location planning. Its main components are including but not limited to inventory, facilities planning establishment, and also transportation (Letmathe & Balakrishnan, 2005; S. Li, 2014). Generally, there are different types of supply chain networks from single objective deterministic distribution network planning up to multi-objective stochastic sustainable supply chain networks. They usually are considered in joint optimizing decisions such as facilities location, amount of right allocation, the level of inventory and an efficient distribution network(Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2018a; Lim, Jeong, Kim, & Park, 2006; Miranda & Garrido, 2004; Samadi, Mehranfar, Fathollahi Fard, & Hajiaghaei-Keshteli, 2018; Selim, Araz, & Ozkarahan, 2008; Shen, Coullard, & Daskin, 2003; Q. Zhang, Sundaramoorthy, Grossmann, & Pinto, 2017). As one of the first and important studies in this area, Sabri and Beamon (Chan et al., 2005) developed a multi-objective supply chain network design model to strategic and operational supply chain and logistic planning. In their research, the structure of supply chain network consists of four echelons from suppliers to customers. Their model provided an efficient performance criterion to analyze the whole network. There are also many studies with different type of location problems along with inventory management decisions. Based on the literature, the economic order quantity (EOQ) model is one of earlier frameworks to support ordering decisions in supply chain networks. In this regard, Daskin et al. (Daskin et al., 2002) applied a Lagrangian relaxation methodology to solve a simple EOQ model. As such, Shen et al. (Q. Zhang et al., 2017) employed a same model and addressed by a hybrid heuristic algorithm based on a branch and bound method. From both of (Daskin et al., 2002) and (Q. Zhang et al., 2017) studies, the clients represent retailers, each of which is a potential candidate for a distribution center. In another similar study, Shu et al. (Shu et al., 2005) developed a novel optimizer to tackle a pricing-based supply chain network. In 2004, Chen and Lee (C.-L. Chen & Lee, 2004) developed a multi-period, multi-stage and multi-product scheduling optimization problem for a multi-echelon supply chain network under uncertainty. In another similar work, Miranda and Garrido (Miranda & Garrido, 2004) presented a methodology to decide on capacitated facilities locations as warehouses and to decide the size of orders. In 2005, Chan et al.,(Chan et al., 2005) also proposed a new approach in GA along with employing analytic hierarchy process (AHP) to solve the same problem in a multi-factory model. Similar to this work, Darvish et al. (Darvish et al., 2016) suggested a multi-echelon supply chain network to optimize simultaneously production decisions, inventory levels and distribution network costs. While Zhang et al. (Q. Zhang et al., 2017) introduced multistage production routing problem that considers the coordination of distribution planning for different goods into many customers, production and routing decisions. An iterative mixed integer linear programming based on a heuristic approach is used to solve the problem.

Regarding the fuzzy-based papers in this area, there are a number of integrating studies. For example, Golmohamadi et al., (Golmohamadi et al., 2017) proposed a fuzzy production-distribution supply chain network using batch transferring. They solved their model by a set of well-known and recent metaheuristics including Variable Neighborhood Search (VNS), Imperialist Competitive Algorithm (ICA), Red Deer Algorithm (RDA) and hybrid algorithm based on RDA. Similarly, in 2017, Sadeghi-Moghaddam et al., (Sadeghi-Moghaddam et al., 2019) proposed a production-distribution supply chain in a fuzzy environment. They also considered different types of discount in their model. To solve this NP-hard problem, they suggested two population-based i.e. Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) and one single point optimizer i.e. Simulated Annealing (SA).

Regarding the capacitated production-distribution systems, Lim et al.,(Lim et al., 2006) developed a model to optimize the capacities of production plants and distribution centers by considering the uncertainty. In 2008, Selim et al., (Selim et al., 2008) presented a multi-objective model as a collaborative production–distribution planning by fuzzy goal programming approach. In another research, Bouchery et al. (Bouchery et al., 2017) discussed about the coordination in supply chain through a centralized solution, where multi-objective optimization is used to decrease the costs and carbon emissions.

Most of recent works concerning uncertainty and stochastic models in the area of production-distribution supply chain network. For instance, Wu and Chang (Wu & Chang, 2004) considered a grey programming approach to optimize an integrated production and distribution network in textile industry under uncertainty. They divided the environmental costs into two main reasons i.e. water resources fees and pollution charges. To compute the unit of production cost, these two factors were formulated. Their main limitation was the decisions variables which are not correlated to the environmental costs, explicitly. As such, the study of Letmathe and Balakrishnan (Letmathe & Balakrishnan, 2005) was another attempt to coordinate the environmental concerns into a production planning system. The main supposition was to consider different technologies to produce a good. These technologies are differed from their resources consumptions and environmental emissions. The goal was to find an interaction between the total revenues and costs. Another supposition which may differ from other works was to consider a set of levels for products demand to be decreased while the environmental emissions have been increased. Recently, in 2018, Fathollahi-Fard et al., (Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018a) proposes a multi-objective stochastic model to formulate a closed-supply chain network design problem considering the environmental dimensions. They applied a Life Cycle Assessment (LCA) framework to assess the environmental legislations of proposed model. They solved their model by four well-know and recent metaheuristics. Accordingly, GA, VNS, Keshtel Algorithm (Noureddine & Oualid) and Virus Colony Search (VCS) have been employed.

In conclusion, similar to mentioned studies, there are many other papers considering the environmental factors in a production-distribution system (Xu, He, Xu, & Zhang, 2017). Therefore, environmentalism for such decision-making systems is consolidated several new insights which have been derived so far in the literature review. These facts keep this research area active and probing new ideas is inevitable.

1.2. Sustainable supply chain considering carbon policies

There are many works concerning the sustainable supply chain network design in the last decades. As explored by Sahebjamnia et al. (Sahebjamnia et al., 2018), only seven papers in high rank related journals have been published between 2015 and 2017 to address the sustainable supply chain network design problem. As mentioned earlier, economic, environmental and social aspects are three main sustainability dimensions. One of suppositions of environmental aspects is considering the carbon policies. In regards to the both single period and single stag, the study of Zhang and Xu (B. Zhang & Xu, 2013) revealed that more efforts on considering carbon emissions to evaluate multi-item supply chain networks are needed to be investigated. In 2017, Xiaoping et al. (Shi, Zhang, & Sha, 2012) studied the same problem to indicate that one of main issues of Pareto improvements in supply chain networks is to consider the green technology. Recently, Hajighaei-Keshteli and Fathollahi-Fard (Fathollahi-Fard & Hajiaghaei-Keshteli, 2018) emphasized that more attempts on the environmental sustainability aspects such as carbon emissions policies are needed to be evaluated. This reason motivate our attempts to contribute a new production-distribution system considering carbon emissions policies.

Based on both multi-stage and single period, Dobos (Dobos, 2007) detailed the effect of emission trade on production-inventory approach. As such, Absi et al. (Absi et al., 2013) analyzed different carbon policies for a lot sizing multi-resource supply chain network design problem. Consequently, Shi et al. (Toptal, Özlü, & Konur, 2014) probed different impacts of carbon banking for an integrated production-distribution-inventory planning system through using an Arrow-Karlin model (Kirkpatrick et al., 1983). More recently, Li (S. Li, 2014) employed a same methodology as introduced by Shi et al., to deteriorate different items with their trade emission for a manufacturing system.

For multi-period and multi-stage, there is only a few works. From a recent study, Ghosh et al. (Ghosh et al., 2016) considered three main carbon emissions for a distribution network design problem. They probed the conflicting between the total cost and environmental emissions.

Another group of papers is mainly focusing on both single stage and infinite planning horizon period. In this regard, Bonney and Jaber (Bonney & Jaber, 2011) proposed a new variant of EOQ to cover the environmental impacts. As such, Hua et al. (Hua et al., 2011) considered the operational activities for a distribution network to find an interaction between economic and green impacts. In another work, Bouchery et al. (Bouchery et al., 2012) considered sustainability criteria for the same model. Similarly, Chen et al. (X. Chen et al., 2013) by using a similar model, compared different carbon emissions. Recently, as a continuation study of (Bonney & Jaber, 2011), Toptal et al. (Toptal et al., 2014) a three-level supply chain network design is developed regarding a new variant of EOQ models. At the last but not the least, Wahab et al. (Wahab, Mamun, & Ongkunaruk, 2011) utilized an integrated approach to cover a variety of defective items by considering return policy based on an EOQ model. There are more other works concerning environmental and sustainable measurements which have been integrated with EOQ and EPQ frameworks (J. Li et al., 2017). This issue indicates the necessity of new optimization model to analyze more the environmental emissions.

Regarding the aforementioned works and to the best of our knowledge, there is no paper in the production-distribution problem that considers (Fard & Hajiaghaei-Keshteli, 2018) the safety stock constraints and the impacts of lead time as well as (Hajiaghaei-Keshteli & Fathollahi-Fard, 2018) considering both overtime and regular production rates. Therefore, the present paper models an integrated supply chain network to cover all production, distribution and inventory planning, simultaneously, with carbon emissions. The proposed sustainable supply chain network can also cover the lead time with regular and over time production rates with several real-life constraints. This paper has both important applied and theoretical contributions. Primarily, the detailed literature review on both production-distribution problem with environmental constraints and sustainable supply chain network by considering lead time and ordering policies. Secondarily, facility locations and their deals with the opened locations are defined. This research formulates a non-linear mixed-integer aggregate the model. Due to its complexity, a set of well-know and recent metaheuristics and a hybrid whale optimization algorithm have been developed as another main contribution of this study. Finally, regarding the model proposed and a set of sensitivity analyses performed, several practical implications are discussed.

2. Problem modeling

This work aims to develop a new sustainable supply chain network with three echelons as a type of location and allocation problems by considering the carbon emissions policies. Generally, the model provides these important factors to design a sustainable supply chain network including the manufacturing cost, the holding cost, the transportation cost, the ordering cost, the regular and overtime of manufacturing process and the environmental emissions regarding the transportation, manufacturing and holding cost of system. As mentioned earlier, there are three carbon emissions policies in this study including strict carbon capping, carbon taxing and considering the cap-and-trade of carbon. In this regard, a Mixed Integer Non-Linear Programming (MINLP) model has been developed with two conflicting objective functions including the minimization the total cost of system and carbon emissions considerations. Overall, there are three echelons in our study including suppliers (A), manufacturers (B) and distributers (C). A planning horizon with multiple time and a set of routings (I) have been considered. In regards to illustrated problem, following assumptions are set for the model proposed:

- There is no flow between the same facilities in each echelon.
- All demand must be satisfied.
- The lead time of manufacturer B to the item I is a fixed parameter.
- The standard normal distribution value is fixed for all members of supply chain network.
- There is no capacity limitation for the order quantity.
- The setup times of products are considered by the times of assembly and obtained shortage item to assemble the eventual products.
- In regards to the flow of this forward supply chain network, a unique output product can be manufactured by each facility B. Each unit of final product may be assembled from multiple units of many input products. Therefore, each facility B can correspond some unit initial products to a unique final product.
- Similar to other production systems, there is only one upstream node for a set of initial input products for each facility B. In this regard, it is possible that there are several upstream nodes for each facility B. There are a group of external suppliers or some other plants for manufacturing. In this case, facility B with several products can be supplied by an external supplier.

Overall, the used sets, parameters and decision variables are presented as follows:

Sets:

A	Suppliers
B	Manufacturers

C	Distributers
I	Items to be supplied to manufacturers
P	Products delivered to distributers
D	Demand
t	Time of periods

Parameters:

LT_{BI}	Lead time
r_{BI}	Reorder point
$Z_{1-\alpha}$	Service level of proposed supply chain
∂_{LT}	Demand variance during the lead time
HC_{BI}	Holding cost of item I at manufacturer B
Q_{BI}	Order quantity for the item I at manufacturer B
OC_{BI}	Order cost of item I at manufacturer B
F_B	Opening cost of manufacturer B
μ_{CP}	Mean demand of products
∂_{CP}	Variance demand of products
HC_{CP}	Holding cost at distributer C for product P
CBpt	Regular time production cost per unit
CCPBt	Cost of per unit over-time production
TCBAI	Cost of transforming each unit item I from supplier A to manufacturer B
TCCBP	Cost of transforming each unit product P from manufacturer B to distributer C
EMFB	Fixed emissions from manufacturer B
EMVB	Variable emissions from manufacturer B
EOFPB	Fixed environmental emissions due to transportation of product P from manufacturer B
EOV_{PB}	Variable environmental emissions due to transportation of product P from manufacturer B
EOFIA	Fixed environmental emissions due to transportation of item I from supplier A
EOVIA	Variable environmental emissions due to transportation of item I from supplier A
EIPC	Environmental emissions due to inventory at distributer C
EIPBt	Environmental emissions due to inventory at manufacturer B
T	Carbon Tax
F	Fine at exceeding carbon cap
Ψ	Trading cost of carbon credits
CCap	Carbon cap
M	A big scalar

Decision variables:

X_B	It gets 1, if the manufacturer B is open; otherwise 0.
Y_{CBP}	It gets 1, if the materials P transported to distributer C from manufacturer B; otherwise 0.
Z_{BAI}	It gets 1, if supplier A serves item I to manufacturer B; otherwise 0.
QRCPBt	Regular time of production quantity

QOCPBt Over-time of production quantity

Here, the proposed formulation has been presented. The model has been inspired by the main previous works in this area i.e. [38-43]. For a distributer, the inventory would be stocked by supplying the demand of customers based on 1-α probability during the lead time LTBI .Therefore, following function may be used to estimate this probability.

$$\Pr(D(LT_{BI}) \leq r_{BI}) = 1 - \alpha \tag{1}$$

where D(LTBI) during the lead time is item demand D. So, as may be seen in the following equation, a normal distribution function is utilized to estimate the reordering point:

$$r_{BI} = E(D_{BI}) \times E(LT_{BI}) + Z_{1-\alpha} \times \sqrt{(ED_{BI})^2 \times \partial_{LT}{}^2 + E(LT_{BI} \times V_{BI})} \tag{2}$$

Similar to other production systems, the variance may be neglected due to the lead time is fixed. As a result, the reordering point can be reconsidered as follows:

$$r_{BI} = D_{BI} \times LT_{BI} + Z_{1-\alpha} \times \sqrt{LT_{BI} \times V_{BI}} \tag{3}$$

where the value of standard normal distribution value is calculated by Z1-α. As suggested in Eq. (3), the computation of holding cost has been illustrated. From the calculation presented by Eq. (4), the first term computes the holding cost average of ordering quantity. As such, the safety stock cost is calculated in the second term.

$$(HC_{BI} \times Q_{BI})/2 + HC_{BI} \times Z_{1-\alpha} \times \sqrt{LT_{BI}} \times \sqrt{V_{BI}} \tag{4}$$

Taken together, all cost of holding and order system can be estimated as seen in Eq. (5).

$$\sum_{B} \sum_{I} HC_{BI} \times Z_{1-\alpha} \times \sqrt{LT_{BI}} \times \sqrt{V_{BI}} + (HC_{BI} \times Q_{BI})/2 + \frac{OC_{BI} \times D_{BI}}{Q_{BI}} \tag{5}$$

As mentioned earlier, there is no capacity constraints in our proposed formulation. Hence, there is a set of differences between Eq. (5) in terms Q and equating it to zero. To do this end, the following formula is calculated:

$$\frac{H_{BI}}{2} + \frac{OC_{BI} \times D_{BI}}{Q_{BI}{}^2} = 0 \tag{6}$$

Based on the Eq. (6), the amount of $Q_{BI}$is equal to:

$$Q_{BI} = \sqrt{\frac{2 \times OC_{BI} \times D_{BI}}{HC_{BI}}} \tag{7}$$

After the calculation of Eq. (7) and Eq. (5), the total cost of production and distribution system can be given in the first objective function as seen in Eq. (8). In this equation, the first term considers the opening cost which is required to open the manufactures. The second term considers the ordering and holding cost of manufacturers. As such, the third term computes the buffer stock holding cost. The knowledge of manufacturing cost for manufacturers is imparted by the fourth term. At the end, the two last terms give the transportation costs between the suppliers and manufacturers as well as the manufacturers and distributers.

$$\begin{aligned}\min Z_1 = {} & \sum_B F_B \times X_B + \sum_B \sum_I \sqrt{2 \times HC_{BI} \times OC_{BI}} \\ & + \sum_B \sum_I HC_{BI} \times Z_{1-\alpha} \times \sqrt{LT_{BI}} \times \sqrt{V_{BI}} + \sum_C \sum_P \mu_{CP} \times HC_{CP} \\ & + \sum_C \sum_B \sum_P \sum_t [QR_{CBPt} \times C_{BPt} + QO_{CBPt} \times C_{CBPt}] + \sum_B \sum_A \sum_I TC_{BAI} \times D_{BI} \times Z_{BAI} \\ & + \sum_C \sum_B \sum_P TC_{CBP} \times \mu_{CP} \times Y_{CBP}\end{aligned} \tag{8}$$

The second objective function is given in Eq. (9). This objective aims to minimize the environmental and carbon emissions of all supply chain network members by using four main parts. The carbon emission of manufacturing activities is accounted by the first part. Both second and third parts support the carbon emission of transportation activities from suppliers to manufacturers and similarly, from manufacturers to distributers. The fourth term of second objective function provides the carbon emissions by the inventory.

$$\begin{aligned}\min Z_2 = {} & \sum_B [EMF_B \times X_B + EMV_B(QR_{CPBt} + QO_{CPBt})] + \sum_C \sum_P \sum_B (Y_{CBP} \times EOF_{BI} + EOV_{PB} \times \mu_{CB}) \\ & + \sum_A \sum_B \sum_I [EOF_{IA} \times Z_{BAI} + EOV_{IA} \times D_{BI}] + \sum_C \sum_B \sum_P (EI_{CP} \times \mu_{CP} + \sum_t EI_{PBt} \\ & \times Z_{1-\alpha} \times \sum_I \sqrt{LT_{BI}} \times \sqrt{V_{BI}})\end{aligned} \tag{9}$$

Regarding the carbon taxation, certain tax may be considered as the total emissions computed by Eq. (9). There is a supposition for each environmental emissions unit to assume we the tax to be τ. Accordingly, Eq. (10) presents the total cost of supply chain system with the supposition of carbon tax:

$$Z_1 + \tau Z_2 \tag{10}$$

As such, there is a limitation for the carbon emissions amount to be under strict carbon policy, there is a constraint on the amount of carbon emitted across the supply chain network under the presented carbon policy. Here, this supposition is existed to impose the cap on the entire of all supply chain network. Assume that Ccap is the amount of carbon cap. Accordingly, a limitation would be considered as follows:

$$Z_2 \leq \text{Ccap} \tag{11}$$

As discussed before, the carbon cap-and-trade policy is also considered by this study. Generally, there are two cases based on a positive and negative value of carbon credit as the result of Eq. 12. If the environmental emissions are greater than the cap, a positive carbon credit would be considered. Conversely, if the environmental emissions are lower than the cap, a negative carbon credit value would be traded.

$$Z_2 - \text{Ccap} \tag{12}$$

If it is assumed that ψ would be the unit carbon emission cost. Accordingly, the total cost of proposed system after the conditions of carbon cap and trade would be as follows:

$$Z_1 + \psi \times (Z_2 - C_{cap}) \tag{13}$$

The other constraints of model can be listed as follows:

$$\sum_B Y_{CBP} = 1;\ \forall C, P \tag{14}$$

$$\sum_A Z_{BAI} = X_B;\ \forall I, B \tag{15}$$

$$\sum_A \sum_I D_{BI} \times S_I \times Z_{BAI} \leq S_{capB} \times X_B;\ \forall B \tag{16}$$

$$\sum_C \sum_P \mu_{CP} \times T_P \times Y_{CBP} \leq P_{capBP};\ \forall B, P \tag{17}$$

$$\sum_C \sum_I \mu_{CP} \times b_{PI} \times Y_{CBP} \leq \sum_I D_{BI};\ \forall B, P \tag{18}$$

$$\sum_C \sum_P \sigma_{CP} \times Y_{VBP} \times b_{PI}^2 = V_{BI};\ \forall B, I \tag{19}$$

$$L_{CP(t-1)} + QR_{CBPt} = L_{nPt};\ \forall C, B, P, t \tag{20}$$

$$\sum_C \sum_P QR_{CBPt} \times T_P \leq T_{PBt};\ \forall B, t \tag{21}$$

$$\sum_P L_{NCPt} \times U_P \leq S_{capC}; \forall C, t \tag{22}$$

$$\sum_t (QR_{CBPt} + QO_{CBPt}) \leq Y_{CBPt} \times M;\ \forall C, B, P \tag{23}$$

$$X_B, Y_{CBP}, Z_{BAI} \in \{0,1\} \tag{24}$$

$$QR_{CBPt}, QO_{CBPt} \geq 0 \tag{25}$$

As detailed by Eq. (14), this constraint guarantees that for all products, the demand of distributers (warehouses) should be satisfied by only one established manufacturer or plant center. As being indicated by Eq. (15), the supplier A must provide its supplying, operationally. As such, Eqs. (15) and (16) also proposed that manufacturer B is restricted by a specific capacity storage and production limitation. To compute the average and variance of production to manufacture at manufacturer B, Eqs. (17) and (18) are provided to do this end. An interaction between the demand of distributors by considering previous, current and the production quantity periods for each product P as the main inventory decisions is considered by Eq. (19). The production quantities restriction during regular and overtime hours are decided by Eqs. (20) and (21). The distributer capacity storage is determined by Eq. (22). To support that a product P can be manufactured by only an opened manufacturer B, Eq. (23) confirms this issue. At the end, the binary variables are guaranteed by Eq. (24). Similarly, the positive continuous variables are ensured by Eq. (25).

To the best of our knowledge, the presented model has not been introduced by a similar study. Hence, the proposed model has addressed a sustainable production-distribution supply chain network with carbon emissions policies. Generally, the simplest case of a location-allocation problem is NP-hard (Fathollahi-Fard & Hajiaghaei-Keshteli, 2018; Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018a). In this regard, the presented model as a type of location-allocation problem is very difficult to solve due to inventory and multi-period decisions as well as considering a multi-echelon supply chain network. Therefore, metaheuristics are needed to be considered for solving such models when especially the size of problem increases. In the following, the proposed solution methodology including three proposed algorithms via their encoding and procedures has been introduced.

3. Solution methodology

Another main contribution of this study is to propose a new hybrid metaheuristic algorithm based on the Whale Optimization Algorithm (WOA) as a recently-developed optimizer and Simulated Annealing (SA) as a well-known algorithm utilized in the literature repeatedly. Accordingly, a comparative study based on these three algorithms i.e. SA, WOA and a Hybrid of WOA and SA (HWS) has been applied. Since the proposed problem is a bi-objective optimization one, this comparison would be based on the Pareto optimal frontier. In this regard, when a solution can dominated another solution, if it has a better value at least in one of objective functions (Fard & Hajiaghaei-Keshteli, 2018). The best solution of algorithms is a set of solutions called Pareto optimal frontier. Since the structure of multi-objective optimizers has been offered by many recent similar studies, interested readers can study their works such as (Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018b; Letmathe & Balakrishnan, 2005). Here, at first, due to continuous search space of metaheuristics as well as encoding the problem, satisfactorily, an encoding scheme has been proposed to transform an infeasible continuous representation to a feasible discrete one regarding the decision variables of model. In addition, the description of applied metaheuristics has been represented as well.

3.1. Encoding scheme of metaheuristics

Similar to most of studies using metaheuristic planning approaches, an encoding scheme is necessary to employ for presented mathematical formulation (Golmohamadi et al., 2017; Sadeghi-Moghaddam et al., 2019). The proposed problem has three main binary decision variables i.e. X_B, Y_{CBP} and Z_{BAI}. Two other continuous variables i.e. QR_{CBPt} and QO_{CBPt}can be calculated based on the binary variables. Among them, X_B is a type of location variables. As such, Y_{CBP} and $Z_{BAI}$are two allocation variables. For both groups, a popular technique called random-key is utilized to transform an infeasible representation to a feasible one. Fig. 1 shows the representation for selection of manufacturers. Regarding this example, there are four potential sites for manufactures and among them, only two of them must be selected to be opened. In the first step, a number of random numbers distributed by uniform function (0, 1) has been generated. Accordingly, if this value greater than 0.5, it get 1 to be considered as an open manufacturer. Otherwise, it gets 0. Notably, the higher values generally get 1. Based on this rule, the second and fourth manufacturer should be opened. More details can be seen in Fig. 1, as well.

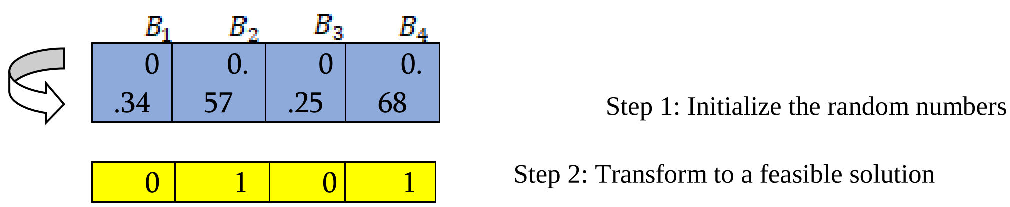


Fig. 1. The used technique for selecting manufactures to be opened

Regarding the allocation variables, based on the located manufacturers, a priority-based representation has been utilized similar to recent similar studies (Golmohamadi et al., 2017). The considered example for representation of allocation has been considered in Fig. 2. There are two suppliers and three distributers by considering two items to be supplied from suppliers to manufacturers as well as four products delivered from manufacturers to distributers. Note that all items and products should be assigned in all levels. Therefore, as represented in Fig. 2, for each selected manufacturer, a number distributed by uniform function (0, 2) is generated. As such, for each distributer, based on the selected manufacturers, a uniform distributed function should be designed. Therefore, from the Fig. 1, a uniform distributer between (1,2) and (3,4) has been considered. Taken together, supplier one has been allocated to both selected manufacturers. As such, the second manufacturer is considered for the first and third distributers. The fourth manufacturer is assigned to the second and fourth distributers, as well. More details are given by Fig. 2.

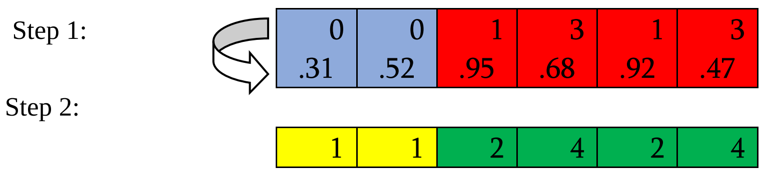


Fig. 2. The used technique for allocation of suppliers to manufacturers and manufacturers to distributers

3.2. Simulated Annealing (SA)

One of well-known techniques among traditional metaheuristics is Simulated Annealing (SA) proposed by Kirkpatrick et al., (Kirkpatrick et al., 1983). This single solution algorithm is inspired by the annealing process of heavy metals. In brief, this algorithm starts with an initial random solution. Based on the local search strategies, a new neighbor solution will be generated. If this solution has a better fitness in comparison with the current one, it would be replaced. Otherwise, regarding an accepting rule based on the fitness evaluations and the current temperature of algorithm, a decision for accepting or rejecting this new solution should be made. Since the proposed problem is a bi-objective optimization one, the structure of accepting or rejecting a new solution would be differentiated and complicated. Regarding the Pareto optimal frontier, a solution replaced another if it can dominated the current one. Otherwise, the Pareto optimal solutions should be updated. The multi-objective version of SA has been employed in many similar studies (Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018b; Hajiaghaei-Keshteli & Fathollahi-Fard, 2018; Letmathe & Balakrishnan, 2005; Samadi et al., 2018). This applied version is similar to them. To address the details of the multi-objective SA, a pseudo-code has been provided as seen in Fig. 3.

Tune the parameters.

Initialize and evaluation fitness functions (x_{old} , $f_j(x_{old})$).

Best solution = (x_{old} , $f_j(x_{old})$).

it=1;
while $it \leq Maxit$
sub=0;
while $sub \leq Subit$
Do one of mutation procedures and generate x_{new}
Calculate the fitness function and (Δf_j)
if $\Delta f_1 \leq 0$ && $\Delta f_2 \leq 0$
    Update the Best solution =(x' , $f_j(x')$)
    Update the solution $x_{old} = x_{new}$
else if $\Delta f_1 \geq 0$ && $\Delta f_2 \leq 0$ || $\Delta f_1 \leq 0$ && $\Delta f_2 \geq 0$
    Put this solution in Pareto set.
else $\Delta f_1 \geq 0$ && $\Delta f_2 \geq 0$
    $P_1 = \exp\left(\frac{-\Delta f_1}{T}\right)$, $P_2 = \exp\left(\frac{-\Delta f_2}{T}\right)$, h=rand
    if h<P_1 && h< P_2
    Update the solution $x_{new} = x_{new}$
endif
endif
sub=sub+1;
endwhile
Update temperature (T=α*T).
Update the non-dominate sorting in this Pareto set.
it=it+1;
endwhile
return the non-dominated solutions;

Fig. 3. Pseudo-code of the applied multi-objective version of SA

3.3. Whale Optimization Algorithm (WOA)

Recent years have observed a rapid development of novel bio-inspired algorithms to solve NP-hard problems. The new characteristics of these optimizers in balancing the search phases i.e. intensification and diversification lead to find the global solutions instead of several local solutions, satisfactorily. One of successful recently-developed metaheuristics called the Whale Optimization Algorithm (WOA) inspired by whales' behavior is proposed by Mirjalili and Lewis (Taguchi, 1986) in 2016. This optimizer has been motivated by several interested researchers i.e.(Fard & Hajiaghaei-Keshteli, 2018; Sadeghi-Moghaddam et al., 2019) to apply and to propose several variants of this algorithm. This metaheuristic uses three main simulation operators of humpback whales including the imagery of prey, encircling prey and bubble-net foraging behavior. Regarding the search phases, the WOA does the intensification properties by encircling prey. As such, the imagery of prey maintains the diversification phase. At the last but not the least, the bubble-net foraging behavior generally performs both exploitation and exploration phases. One of the main benefits of WOA for users is that this metaheuristic is simple to tune by using only two input parameters. The related formulation of these operators can be referred to (Taguchi, 1986). As mentioned earlier, a multi-objective version of WOA is needed to be investigated. Similar to other population-based technique, selecting the next generation of algorithm is challengeable to solve a multi-objective optimization problem. Accordingly, the non-dominated sorting is characterized for the considered WOA similar to (Fard & Hajiaghaei-Keshteli, 2018) and (Taguchi, 1986). Generally speaking, the details of considered multi-objective WOA are provided by a pseudo-code as seen in Fig. 4.

```
Tune the parameters of WOA.
Initialize the whale's population.
Calculate the fitness of each search agents by considering the proposed encoding schemes.
Set the Pareto optimal solutions.
while (t< maximum number of iteration)
    for each search agent
        Update A, a, C, l, and p; */they are some random parameters of WOA/*
        if1 (p<0.5)
            if2 (|A|< 1)
                Update the position of current search agent by Encircle prey.
            elseif2 (|A|> 1)
                Select a random search agent;
                Update the position of current search agent by search for prey.
            endif2
        elseif1 (p≥0.5)
            Update the position of current search agents by spiral updating position.
        endif1
    endfor
    Check if any search agents goes beyond the search space and amend it.
    Update the Pareto optimal frontiers.
    t=t+1;
endwhile
return the non-dominated solutions;
```

Fig. 4. The pseudo-code of applied multi-objective of WOA

3.4. Hybrid of WOA and SA (HWS)

As detailed earlier, one of main improvements of this proposal is to propose a new hybrid metaheuristic based on WOA and SA called as HWS. Generally, the proposed HWS considers WOA as the main loop and SA as the local loop. The properties of SA motivated several related researchers to employ this algorithm in their proposed hybrid methods as a local search improvement. In the developed HWS, instead of spiral updating positions of each search agent, a local search based on SA is considered for each agent. Actually, in the proposed algorithm, SA does the local search based on the spiral procedures and accepting and or rejecting of solutions have been formulated regarding the SA structure. Based on our treatments, this SA rules help the algorithm to improve both intensification and diversification phases. Except of this operation of WOA, the other steps of HWS is completely similar to the main original idea of WOA. Note that this applied optimizer is also developed in a multi-objective version. To consider more details about the proposed HWS, its pseudo-code is provided as seen in Fig. 5.

```
Tune the parameters of HWS.
Initialize the whale's population.
Calculate the fitness of each search agents by considering the proposed encoding schemes.
Set the Pareto optimal solutions.
while (t< maximum number of iteration)
    for each search agent
        Update A, a, C, l, and p; */they are some random parameters of WOA/*
        if1 (p<0.5)
            if2 (|A|< 1)
                Update the position of current search agent by Encircle prey.
            elseif2 (|A|> 1)
                Select a random search agent;
                Update the position of current search agent by search for prey.
            endif2
        elseif1 (p≥0.5)
            Do the spiral updating procedures and generate x_new for each search agent.
            if Δf1 ≤ 0 && Δf2 ≤ 0
            Update this search agent
            else if Δf1 ≥ 0 && Δf2 ≤ 0 || Δf1 ≤ 0 && Δf2 ≥ 0
            Put this solution in Pareto set
            else Δf1 ≥ 0 && Δf2 ≥ 0
            P1 = exp(-Δf1/T) , P2 = exp(-Δf2/T) , h=rand
                if h<P1 && h< P2
                Update this search agent
                endif
        endif1
    endfor
    Check if any search agents goes beyond the search space and amend it.
    Update T and its reduction rate.
    Update the Pareto optimal frontiers.
    t=t+1;
endwhile
return the non-dominated solutions;
```

Fig. 5. The pseudo-code of proposed multi-objective of HWS

4. Experimental results

In this section, first of all, a set of data with different instances has been generated. Consequently, based on the generated data, the proposed optimizers should be tuned to select a set of proper values to improve the performance of applied metaheuristics. Accordingly, a comparative study has been designed to evaluate the effectiveness and efficiency of obtained optimizers in different criteria and measurements. To validate the proposed model, a set of sensitivity analyses based on the key parameters of considered model has been extended. Finally, based on the sensitivity analyses and the results of proposed optimizers, the managerial implications of this study has been recommended, as well.

4.1. Instances

Since this paper is the first attempt to develop a sustainable production-distribution supply chain network with all location, allocation and inventory decisions under carbon emissions policies in a three echelons, there is no similar problem from the literature to use their data. Accordingly, the test problems have been generated by using an approach based on similar papers (Fathollahi-Fard & Hajiaghaei-Keshteli, 2018; Letmathe & Balakrishnan, 2005).

To evaluate the applied optimizers with different complexities, 15 test problems in three classifications i.e. small, medium and large scales are introduced as given in Table 1. The surfaces of model's parameters are computed as illustrated in Table 2. Note that all fixed and variable environmental emissions have been benchmarked by using an approach proposed in (Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018a). The details of parameters were given in Section 2.

Table (1): Problem instances

Classification	No. of problem	A	B	C	I	P	D	t
Small	P1	2	4	4	4	10	10	3
	P2	2	6	6	5	12	20	3
	P3	6	8	8	6	14	30	3
	P4	6	10	12	7	16	40	4
	P5	6	12	16	8	18	45	4
Medium	P6	10	12	20	10	20	60	4
	P7	10	12	26	10	22	70	6
	P8	10	14	32	10	24	80	6
	P9	10	14	38	11	26	90	6
	P10	10	16	44	12	28	100	8
Large	P11	15	20	50	14	30	130	8
	P12	15	22	54	15	32	150	8

P13	15	24	60	16	34	160	10
P14	15	26	70	17	36	170	10
P15	15	30	80	18	38	200	10

Table (2): Parameters and their surfaces

Parameter	Surface
∂_{LT}	U(0, 2)
HC_{BI}	rand{5, 10, 15, …50}
Q_{BI}	rand{100, 150, …, 1000}
OC_{BI}	rand{20, 30, 90}
F_{B}	rand{50, 100, 150, …}
μ_{CP}	U(500, 1000)
∂_{CP}	U(1, 10)
HC_{CP}	rand{5, 10, 15, …50}
CBpt	rand{1000, 1100, …, 10000}
CCPBt	rand{1000, 1100, …, 10000}
TCBAI	rand{1, 2, 3, …6}
TCCBP	rand{1, 2, 3, …6}

4.2. Tuning of metaheuristics

Since given optimizers have a number of parameters to tune, it is necessary to set their parameters, comprehensively, to increase their performance (Golmohamadi et al., 2017; Sadeghi-Moghaddam et al., 2019). To tune the algorithms, Taguchi method has been considered. As discussed earlier, the evaluation of metaheuristics for a multi-objective optimization model is different. A number of efficient evaluation metrics is required to assess the metaheuristics in an efficient way. Considerably, this study utilizes four well-known evaluation metrics including Number of Pareto Solutions (NPS) (Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018b; Samadi et al., 2018), Mean Ideal Distance (MID) (Fathollahi-Fard & Hajiaghaei-Keshteli, 2018; Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018a), Spread of Non-dominance Solution (SNS) (Fard & Hajiaghaei-Keshteli, 2018; Hajiaghaei-Keshteli & Fathollahi-Fard, 2018) and Maximum Spread (MS) (Letmathe & Balakrishnan, 2005; S. Li, 2014). Thus these metrics are well-known and have been utilized in several studies, more explanations along with their formulations are referred to their main papers such as (Fathollahi-Fard, Hajiaghaei-Keshteli, et al., 2018b; Sahebjamnia et al., 2018).

Regarding the collaboration of optimizers, Taguchi method divides the properties of collaboration into two categories i.e. noise and control factors. Based on the noise factors, Taguchi employs signal-to-noise (S/N) to compute the response variation values of optimizers (Abdi, Abdi, Fathollahi-Fard, & Hajiaghaei-Keshteli, 2019; Bahadori-Chinibelagh, Fathollahi-Fard, & Hajiaghaei-Keshteli, 2019; Buddala & Mahapatra, 2019; Fu, Tian, Fathollahi-Fard, Ahmadi, & Zhang, 2019). Since the model is a case of minimization, the lower value of S/N is more preferable. To calculate the S/N, following formulation has been considered in this regard:

$$S/N = -10 \times \log_{10}\left(\frac{\sum_i {Y_i}^2}{n}\right) \tag{26}$$

where n is the orthogonal arrays number and Y_i is the response value of i^{th} orthogonal array. Similarly, regarding the control factors, Eq. (27) represents a selected response value based on the characteristics of bi-objective optimization model. Based on the results of MID and MS metrics as the convergence and diversity metrics, a new metric called as MCOV to control the responses of optimizers (Buddala & Mahapatra, 2019; Hapsari, Surjandari, & Komarudin, 2019) is as follows:

$$MCOV = \frac{MID}{MS} \tag{27}$$

Each parameter of optimizers is a factor with some candidate values as the levels of each factor. Based on the previous studies and our experiences, Table 3 gives the factors of each algorithm along with their candidate levels. The aim is find the best level for each factor. As introduced before, this study applies three metaheuristics called SA, WOA and HWS. The SA has five factors along with three levels for each of them. In this regard, the total number of treatments for SA is 3^5=243. The WOA has two factors with five levels. Accordingly, the total number of experiments is 5^2=25. As such, the HWS has four factors and levels. Hence, its total treatments equal to 4^4=256. Note that since metaheuristics are a variation of stochastic optimization in nature. Each optimizer must run for 30 times and their averages should be considered for each treatment of tuning. Overall, there are many treatments to do for tuning of optimizers

One of the main benefits of Taguchi method is to save the time of users by proposing some orthogonal arrays to reduce the number of experiments (Bahadori-Chinibelagh et al., 2019). Based on the total number of treatments calculated above, the Taguchi method can offer L_{27} for SA to reduce its total experiments from 243 to 27 treatments. In addition to SA, the orthogonal array of L_{25} should be considered for WOA. Since its total experiments are not very high i.e. 25, its total number of experiments has not been changed. At the last but not the least, Taguchi method suggests L_{16} for proposed HWS to decrease its total from 256 to 16. Based on the trial of each orthogonal arrays, the responses should be calculated for 30 run times and the metrics should be computed, as well.

As a result, the tuned parameters of applied optimizers are given in Table 4. Notably, due to page limitation, the results of S/N ratio and MCOV have not been reported and can be presented upon request of interested readers.

Table (3): Factors of optimizers and their levels.

Optimizer	Factor	Levels				
		1	2	3	4	5
SA	A: Maximum iteration (Maxit)	1000	1500	2000	-	-
	B: Sub-iteration (Subit)	20	30	50	-	-
	C: Used methodology of local search (T_m)	Swap	Reversion	Insertion	-	-
	D: Initial temperature (T0)	1000	1500	2000	-	-
	E: Rate of reduction (R)	0.85	0.9	0.99	-	-
WOA	A:Maximum iteration (Maxit)	200	400	600	1000	1500
	B: Population size (nPop)	50	100	150	200	300
HWS	A:Maximum iteration (Maxit)	300	600	800	1200	-
	B: Population size (nPop)	50	100	150	200	-
	C: Initial temperature (T0)	1000	1200	1500	2000	-
	D: Rate of reduction (R)	0.85	0.88	0.9	0.99	-

Table (4): Tuned parameters

Algorithm	Parameters
SA	Maxit=2000; Subit=30; T_m=Reversion; T0=2000; R=0.99;
WOA	Maxit=1000; nPop=200;
HWS	Maxit=1200; nPop=200;T0=2000; R=0.99;

4.3. Comparison of obtained algorithms

Here, a comprehensive comparison has been performed to assess the effectiveness and efficiency of optimizers applied. This comparative section is based on the evaluation with four assessment metrics of Pareto optimal frontier i.e. NPS, MID, SNS and MS. All results are provided for each metric, separately, as seen in Table 5. The computational time behavior for applied optimizers is depicted by Fig. 6. Another criterion is to compare the Pareto optimal frontier of algorithms as given in Fig. 7 for a sample test problem. Finally, some statistical analyses by using LSD intervals are evaluated as seen in Fig. 8.

From the Table 5, the results obtained by each algorithm based on the evaluation metrics under each instances are reported. The best values in each test problem are revealed in bold. Except the MID, for other metrics, higher values are more preferable. Meanwhile, the lower value of MID brings the better capability of algorithms. Overall, from the tables, the proposed HWS shows a better performance in comparison of other algorithms.

Table (5); Comparison of applied optimizers based on the evaluation metrics of Pareto optimal frontiers

Test problem	NPS			MID			MS			SNS		
	SA	WOA	HWS	SA	WOA	HWS	SA	WOA	HWS	SA	WOA	HWS
P1	5	**9**	8	2.3656	**1.4909**	2.1668	322971	364337	**367835**	**357683**	284855	252546
P2	9	**11**	**11**	2.1409	**1.1119**	1.1781	583346	**673114**	659895	699981	**786742**	696675
P3	6	12	**13**	3.0635	2.1143	**2.0267**	674618	**724566**	711843	889612	981314	**996440**
P4	8	11	**12**	4.6701	3.6118	**2.1146**	756024	**1017213**	995784	1500420	1400858	**1634697**
P5	9	12	**13**	2.9635	3.6959	**2.6112**	894850	574956	**1525546**	2355835	2136201	**2484306**
P6	9	**13**	12	5.7248	3.1876	**2.8049**	1261434	968246	**1545794**	**2701689**	2586113	2481696
P7	10	11	**12**	7.3716	**5.0146**	5.4399	1053899	1057282	**1129750**	3219535	**3467159**	2868420
P8	11	13	**14**	**4.5463**	5.8759	5.6609	1035657	919442	**1129797**	3463876	**3718771**	3506257
P9	12	**14**	12	6.8472	4.8438	**4.0797**	1506496	**1865527**	1855450	5140232	**5409774**	5375823
P10	10	**14**	12	3.6925	3.9634	**3.1708**	1750385	1839931	**2248624**	5210873	5702810	**5973421**
P11	11	14	**15**	5.7481	5.8276	**4.0531**	1668077	1399581	**2302254**	5185450	6044003	**6090874**
P12	8	13	**14**	**2.6435**	4.8701	6.3874	1585811	**1761960**	1457975	5801526	**6319580**	6249123
P13	10	**15**	**15**	3.2891	4.2675	3.2895	1547389	1475869	**1563762**	5833145	6657432	**7057842**
P14	11	**16**	**16**	4.4763	4.9788	3.8537	1453687	1564587	**1674284**	5437869	6935741	**7125647**
P15	10	15	**16**	5.8767	4.4633	**3.1704**	1546738	1564372	**1748523**	6647315	6457823	**6962358**

As depicted by Fig. 6, there is a set of similarities between the behaviors of algorithms. From the minimum computational time, the SA is the best optimizer. Its efficiency especially in large-scale instances is highly differentiated from other algorithms. Both WOA and HWS has a set of similarities for small and medium test problems. Except a few test problems, the average time of HWS is clearly more than WOA in most of case studies.

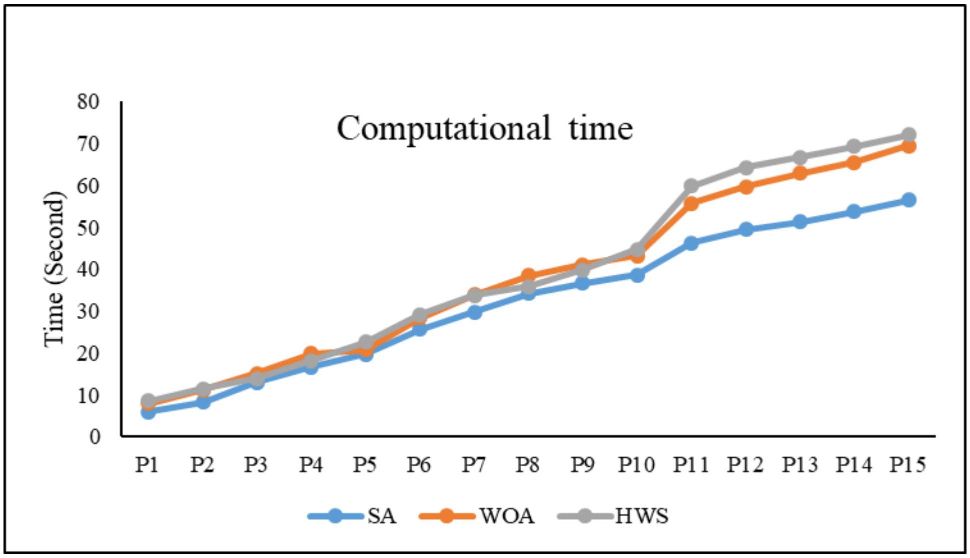


Fig. 6. Behavior of algorithms in term of computational cost

As shown in Fig. 7, the diversity of HWS's solutions are more than other algorithms. The main reason behind of this issue is that the proposed HWS can use the benefits of both SA and WOA to extent its solution and find a better Pareto optimal set. Overall, the proposed HWS can outperform and dominated the most of solutions of two employed optimizers i.e. SA and WOA.

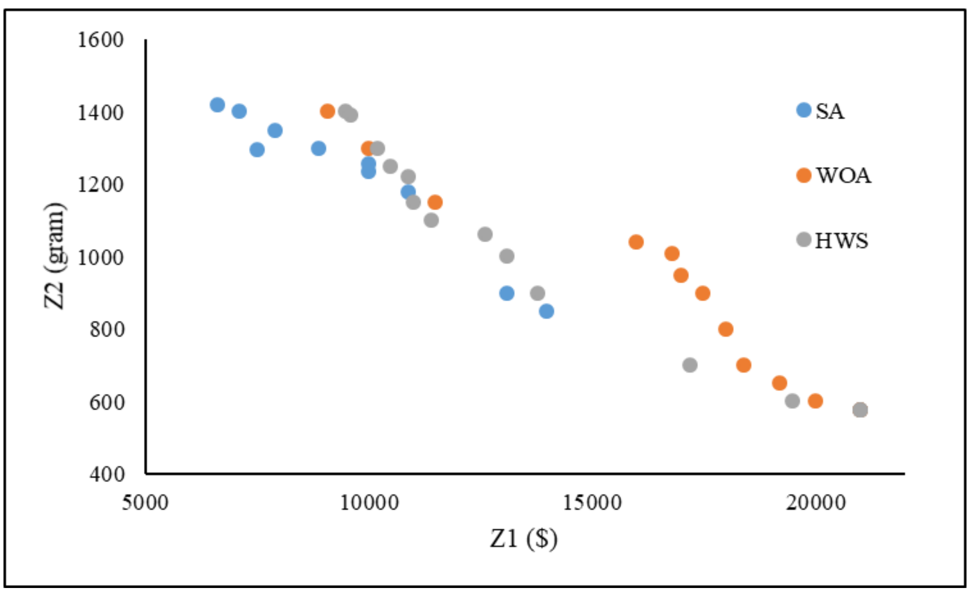


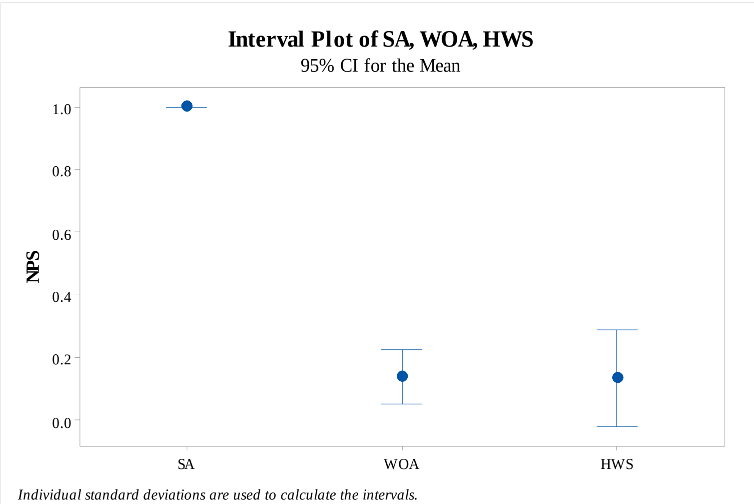
Fig. 7. Pareto optimal frontier in P8 for applied optimizers

Finally, to reach the best optimizers, decisively, some statistical analyses based on LSD intervals have been conducted for each evaluation metrics of Pareto optimal frontiers. The outputs given in the Table 5 are transformed into a popular measurement called the Relative Deviation Index (RDI) as following formula:

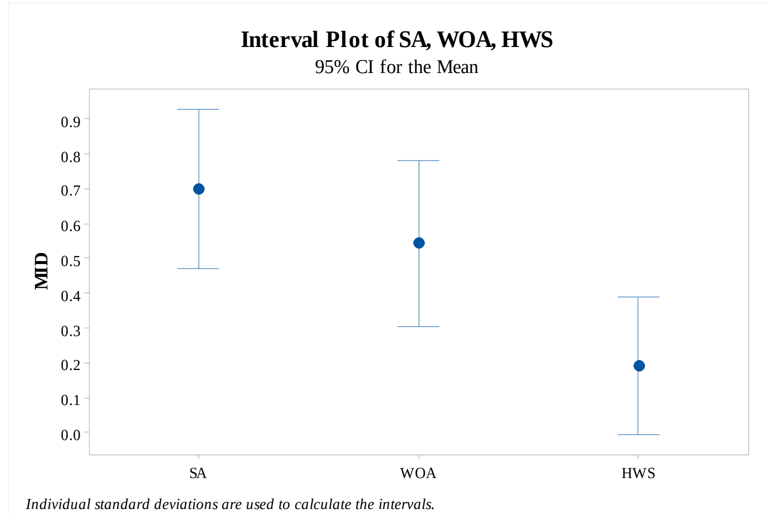
$$RDI = \frac{|Alg_{sol} - Best_{sol}|}{Max_{sol} - Min_{sol}} \tag{28}$$

where Alg_{sol} has been considered as the value of objective function employed by an assessment metric for each algorithm. As such, Max_{sol} and Min_{sol} are the maximum and the minimum values obtained by optimizers, respectively. Similarly, $Best_{sol}$ can be considered as one of Max_{sol} and Min_{sol} due to metrics' nature. As it may clear, the lower value of RDI is more preferable. Generally, based on this measurement, Fig. 8 divides into four sub-figures to show the LSD interval regarding each assessment metric. Regarding the NPS (Fig. 8(a)), there is a clear difference between the performance of SA and two other algorithms. As can be seen, the SA is the worst optimizer. However, WOA is slightly better than WHS in this item. Based on the MID (Fig. 8(b)), it can be resulted that the proposed HWS is clearly outperformed both WOA and SA. As such, the SA brings the worst capability in this analysis. Similar to the MID, as can be seen from the MS (Fig. 8(c)), the HWS is generally better than other metaheuristics. At the last, as can be resulted from the Fig. 8(d), the results of SA in the issue of SNS is the worst behavior. In addition, there is a set of similarities between the WOA and HWS. But, the WOA is better than the HWS in this case.

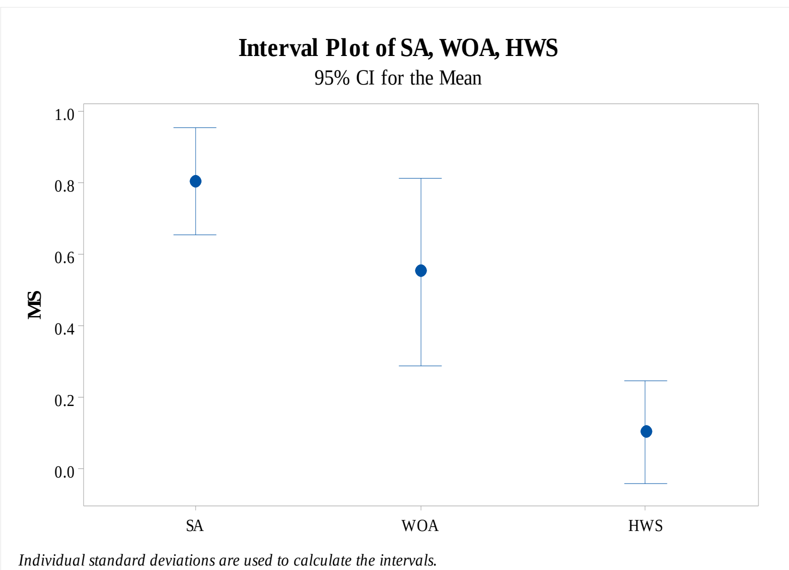
Overall, the performance of both WOA and HWS provides a competitive results. Although the WOA shows a better performance in term of NPS and SNS, the proposed HWS generally outperform the other algorithms. Note that the main demerit of HWS is the computational time of algorithm.



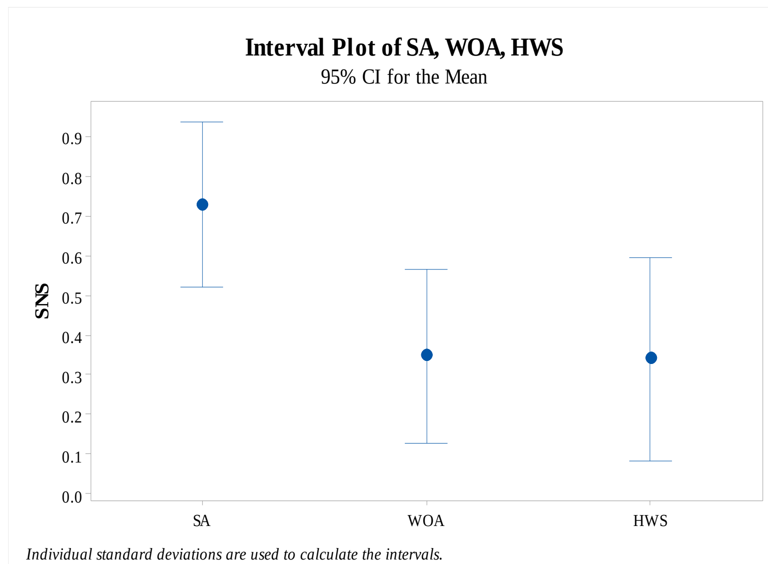
(a)



(b)



(c)



(d)

Fig. 8. LSD intervals based on the RDI

4.4. Sensitivity analyses

Some sensitivities have been performed to evaluate the key parameters to identify the behavior of algorithm. Accordingly, the proposed HWS as the best technique in this study is considered. The results have been checked with Epsilon Constraint (Kirkpatrick et al.) method similar to recent studies e.g. to identify the high-efficiency of metaheuristics. In this methodology, one of objectives is considered as the main goal function. Other objectives have been employed as a set of constraints to check the optimal bounds of model. Based on our results, in all experiments, the proposed HWS reaches a same solution similar to EC. Due to page limitation, this validation has not been reported and can be presented upon request by interested readers.

Here, the main parameters including varying of demand and fixed variance, varying of lead time, the rate of carbon cap-and-trade and the rate of carbon cap are analyzed. In this regard, by increasing the rate of these parameters, both objective functions i.e. Z1: total operational cost and Z2: total carbon emissions are evaluated. Considerably, all treatments are reported in Fig. 9-12.

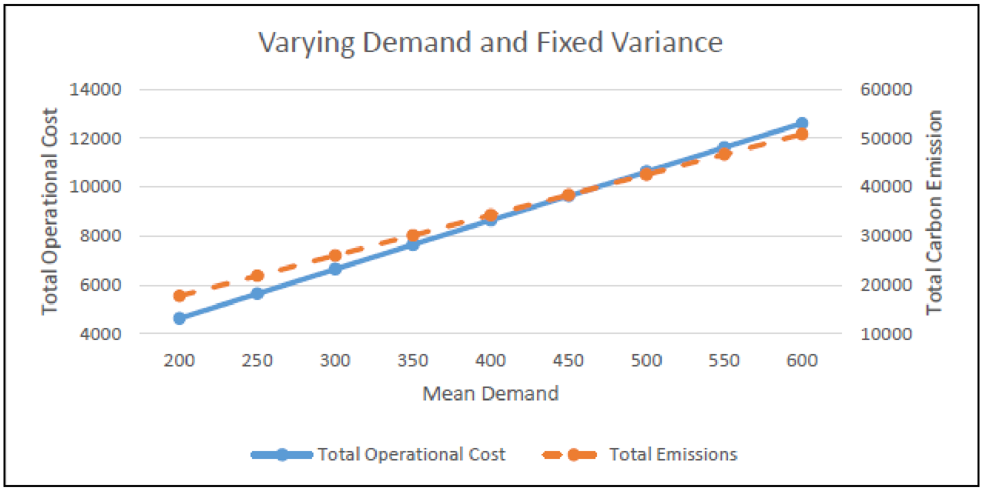


Fig. 9. Impact of mean demand on the objective functions

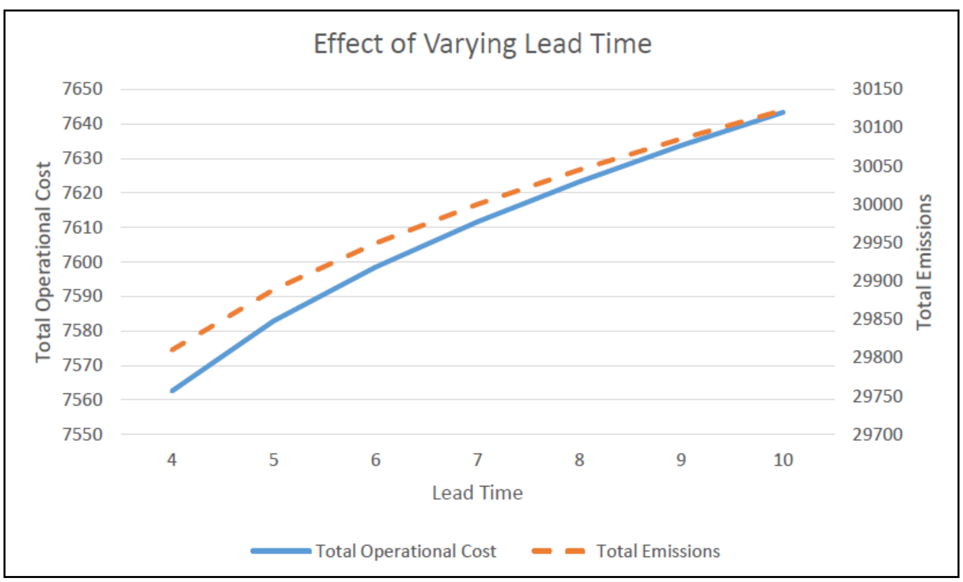


Fig. 10. Impact of lead time on the objective functions

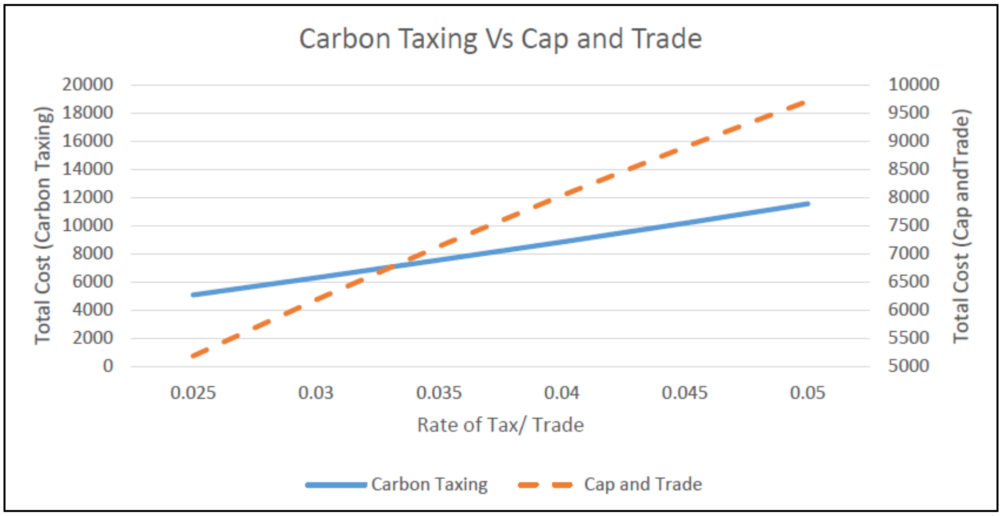


Fig. 11. Impact of variance taxation and carbon trading price on the objective functions

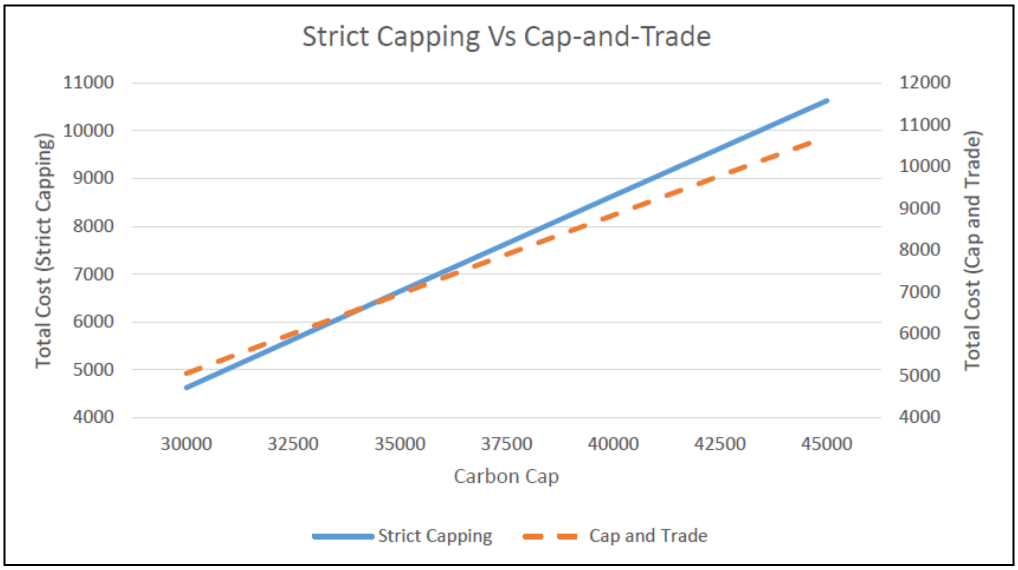


Fig. 12. Impact of changing carbon cap on the objective functions

From Fig. 9, there is a clear relation between the total operational and emissions costs and the mean demand of customers. By considering a fixed variance, the average of demand in the proposed supply chain network would be varied, exponentially. If an increase in the amount of distributor demand to the manufacturer is occurred, the cost of each activity involved in the proposed system would be increased, as well. Overall costs of system have been increased, uniformly. Similarly, based on the environmental emissions, the mean customer demand can affect many parts of the proposed model. Since the model is a type of linear proportional dependence on demand of customers, both behaviors of objective functions are clearly uniformly linear.

As can be seen from Fig. 10, the lead time may be increased, if a change in the total environmental emissions and the total operational costs are occurred. To compare with the mean and variance of demand, lead time shows a less important to make a change on the system. From the aspect of environmental emissions and total operation costs, there is a non-linear relation to increase while the lead time increases. For the large amounts of lead time, it is evident that both total operational and emissions costs reach a high equal growth.

What can be envisaged at the first glance of Fig. 11 confirms that there is a directly relation between the increase of carbon trading cost or carbon taxation and the amount of total cost for all components of system. Clearly, an increase in the amount of carbon trading leads to an increase in the amount of total cost of system. This issue is a little different under carbon cap-and-trade. Generally, the opportunity to sell the credits which are unutilized would be available, if the amount of emissions are low. This reason motivates the carbon cap-and-trade to be beneficial, financially. As may be indicated from this graph, it is observed that when the rate of carbon would be increased, both policies employed show a higher cost. Conversely, regarding the cap and trade system, the carbon taxing would be lower, comprehensively.

As can be resulted from Fig. 12, it is generally an impact on the amount of total cost and the rate of carbon cap under the limitation carbon cap-and-trade policy. Here, there is a variation of carbon cap and the amount of total cost. From the smaller amount of caps, the capping limitation is lower for the total cost, marginally. When the cap increases, it is observed that carbon cap-and-trade would be more efficiently. There is a set of changes on the amount of cap which could lead to a significant result on the all components of distribution network based on the restriction of carbon capping. Overall, these changes make the model to be safer to select the carbon cap and trade, efficiently.

Generally speaking, based on the several analyses done from the aforementioned discussion, it is obvious that the carbon cap-and-trade is the most efficient policy among all. Regarding the managerial implications of this study, we should say that the carbon taxing system is completely needed for all production-distribution systems. Based on main changes addressed by presented graphs, it is proved that the best way to reduce carbon emissions is cap-and-trade. For the developing countries, one of the main contributions would be to consider all economic and environmental aspects by a mechanism of carbon cap-and-trade to set of regular policies.

5. Conclusion and future works

Generally, decision makers in supply chain systems face many challenges in the sustainable supply chain management. During the study of literature on carbon policies for multi-level supply chain network design, we explored a coordinated carbon policies in a supply chain system, which helps organization to design a supply chain based on economic advantages and environmental benefits. The review of extant literature revealed that the supply chain activities including but not limited to manufacturing, transportation and inventory planning are the core reasons of carbon emission. Taking all of this into account, this finding motivated us to propose an integrated supply chain based on both production and distribution models for a forward supply chain network based on the environmental aspects with uncertain customer demands. The model provided was included the location of manufacturers, allocation, and the inventory decisions of different items of products. Whole of them were formulated by a mixed integer non-linear programming model. The main contribution of model was to add three different carbon emission policies for a forward supply chain network design problem considering lead time constraints.

Another main novelty of this study was to develop a new hybrid metaheuristic algorithm called as HWS based on the WOA and SA. This algorithm was compared with its original ideas i.e. WOA and SA. The algorithms were tuned by Taguchi method. In addition, four well-known multi-objective assessment metrics were utilized to evaluate the algorithms with a comprehensive analysis. Based on the statistical analyses, the proposed HWS outperform two other algorithms and give the competitive results. Based on the sensitivity analyses, the correlation of environmental emissions and some main decisions of an economic supply chain network to cover the activities of distributing, manufacturing and storing have been analyzed. In addition, the impact of lead time on the environmental emissions along with distribution policy, and three-echelon supply chain system were evaluated through a set of test problems with different difficulties. Taken together, these considerations in a forward supply chain network design give this ability to have a comparison with three carbon policies employed by this paper. Among them, carbon cap-and-trade may be more beneficial for such systems.

There are several recommendations and suggestions from both aspects of contributions of model and solution methodology. From the aspect of modeling approach, a real case study can be recommended to do more analyses on the proposed model. Routing decisions can be considered into our model. The reverse logistics activities can be ordered to be added into the developed model. As such, more analyses can be suggested for the proposed hybrid approach. Some other large-scale optimization problems can be applied to assess the proposed hybrid algorithm. The effect of tuning for the proposed hybrid method would be also intersecting for the future works.

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