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Carbon-capped Distribution Planning: A JIT Perspective

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ABSTRACT

Products distribution and transportation is one of the largest sources of CO_2 emission in supply chains. To date, a number of researchers have argued that intensive transportation activities through popular distribution strategies such as Just-In-Time (JIT) could significantly increase carbon emissions within logistics chains. However, a systematic understanding of how JIT distribution affects carbon emissions is still lacking in current literature. In this study, we develop a bi-objective optimization model for a carbon-capped JIT distribution of multiple products in a multi-period and multi-echelon distribution network. The aims are to jointly minimize total logistics cost and to minimize the maximum carbon quota allowed per period (carbon cap). The considered problem is investigated under three different carbon emission constraints namely periodic, cumulative and global. Since the studied problem is NP-Hard, a non-dominated sorting genetic algorithm-II (NSGA-II) is developed and its parameters are tuned by Taguchi method. For further quality improvement of the developed solution approach, a novel local search approach called modified firefly algorithm incorporates NSGA-II. Different sizes of the problem are considered to compare the performances of the proposed hybrid NSGA-II and the classical one. Finally, the results are presented along with some policy and managerial insights. For policy makers, the findings show the impact of varying the carbon emission cap on total cost and total emissions under JIT distribution concept. From managerial perspectives, we analyze the relationships between average inventory holding and backlog level per period which can assist mangers to identify critical decisions for JIT distribution of products in carbon-capped environment.

1. Introduction

The environmental protection concerns and legislation are pushing companies to redesign and planning their activities in an environmental friendly manner. This will probably be done by constraining companies to emit less than a given amount of carbon dioxide by product unit that is produced and transported. Upon this direction, some companies may volunteer to reduce their carbon footprint. Voluntary programs like the Montreal Climate Exchange in Canada and Chicago Climate Exchange in US are some examples of this trend. Consequently, companies will face new constraints that will force them to reduce carbon emissions while still minimizing production and transportation costs.

Transportation is at the heart of logistics activities and is one of the leading sources of greenhouse emissions and environmental pollution which account for the largest share of the freight-related emissions (Piecyk & McKinnon, 2010) and emitted carbon dioxide through transportation activities accounting for almost 80% of total greenhouse gas (GHG) emissions (Li, Lu, Zhang, & Wang, 2013). Along this line, the need of some popular strategies such as Just-In-Time (JIT) for transporting small batch sizes seems against environmental protection. More specifically, the JIT principles favor small and frequent deliveries by many small rush transports with multiple regional warehouses. This practice could have a significant effect on the emitted carbon dioxide by a firm through distribution of products. More recently, in literature, there is evidence from empirical studies which confirmed the negative environmental influences using JIT logistics (Arvidsson, Woxenius, & Lammgård, 2013; Govindan, Azevedo, Carvalho, & Cruz-Machado, 2014; McKinnon & Piecyk, 2009). These authors point out that the use JIT increased emissions particularly from transportation, but these investigations rely too heavily on empirical analysis.

In modeling of JIT distribution networks, the most frequently applied objectives are related to cost and service level. In addition, the considered constraints have been generally applied due to

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limitations in capacity. Incorporation of environmental objectives and constraints will generate new problems resulting in new combinatorial optimization models. On the other hand, they add to the model complexities. Both areas require to be investigated.

Motivated by abovementioned issues, in this paper, we study a bi-objective carbon- capped logistic model for a JIT distribution that takes into account different carbon emission constraints. The objectives include the minimization of total costs and minimization of carbon cap. In addition to capacity constraints, three carbon constraints namely periodic, cumulative and global are imposed separately into the considered multi-period three-echelon logistics network that includes multiple plants, multiple distribution centers, multiple retailers and multiple products under JIT distribution.

2. Literature review

In this section, first we provide a review on recently published papers that examine JIT in distribution network planning. Then, in next subsection, we investigated researches that have considered carbon emissions in production and/or distribution planning problems.

2.1. Optimizing and planning of distribution networks under JIT strategy

Among conventional supply chain processes, distribution is known as the products and materials flow between a company and its customers or suppliers. The design and planning of distribution networks have attracted the interest of many studies in the literature (Amiri, 2006; Çelebi, 2015; Manzini, Accorsi, & Bortolini, 2014; Pishvaee, Farahani, & Dullaert, 2010; Selim and Ozkarahan, 2008). JIT distribution plays a key role in efficient distribution of products, both from customers satisfaction view by increasing the service level and cost reduction perspective (Farahani & Elahipanah, 2008). In a JIT policy, each manufacturer must supply the right quantity of products, at the right time to the right locations. This practice leads to reduced storage costs and increased transportation costs.

In the literature, both single and multi-objective optimization have been considered for different distribution network models under JIT logistics. The concept of JIT distribution is often embedded into models by means of earliness and tardiness costs, since these are two very important aspects in filling JIT delivery due dates. Early delivery of finished products may cause customers not to utilize the products, or even decline to receive them. Thus, the supplier or manufacturer may have to store the products in its own warehouses, or extra holding costs are incurred to store them in another organization's warehouses. Similarly, late deliveries may put customers in a position of shortage which can be in the form of either back-order costs or lost sales costs. In addition, suppliers or manufactures may induce penalty costs for early or late deliveries.

For example, Wang, Fung, and Chai (2004) proposed a multiple plants, multiple warehouses and multiple retailers supply network under JIT distribution network. In their model, products are kept in warehouses temporarily prior to delivery to retailers. Each warehouse can serve multiple retailers based on their needs. They sought a system that could deliver the needed amount of products for the retailers on time. When confronted with shortages in capacity, warehouses have to supply the retailers either earlier or later. The holding and backorder costs for retailers are considered as proportional to the varied supplying costs of products from different warehouses. The optimization criteria were the product's inventory levels in the warehouses at different periods. Then, the linear single-objective model which minimizes the total costs was solved by a simplex procedure.

Farahani and Elahipanah (2008) developed a bi-objective model for JIT distribution planning in a three-echelon supply chain. The objectives are: (i) total cost minimization, and (ii) minimization of the sum of backorders and surpluses of products throughout all periods. The second objective denoted the JIT delivery by minimizing the backorders and surpluses amounts of products. The proposed multi-channel, multi-product and multi-period model is formulated as a mixed-integer linear programming (MILP) problem. A multi-objective genetic algorithm (MOGA) was proposed for finding a set of non-dominated solutions.

More recently, Ghasimi, Ramli, and Saibani (2014) developed a single objective MILP model to optimize a JIT distribution network of defective and scrap products. The considered network consists of multiple plants, multiple distribution centers and multiple retailers. The proposed model was formulated as a single-objective optimization to minimize the costs associated with production, distribution, holding and retailer shortages. A genetic algorithm (GA) was proposed to find near optimal solutions for the proposed model.

2.2. Optimizing carbon emission across supply chain networks

To date, a number of studies have developed a mathematical programming approach to deal with carbon emissions in supply chain (SC) networks. Many of these modeling efforts focus on strategic decisions such as the design of SC networks, while challenges at the tactical and operational planning levels are less explored (Govindan, Soleimani, & Kannan, 2015).

The published green SC models can be classified into two main categories. The first category includes modeling efforts with no specific focus on the regulatory schemes, but only trying to minimize the SC environmental impacts including carbon emissions. In this category, generally, a SC network has been formulated as a bi-objective optimization model and the problem is to find a balance between economic and ecological concerns. Economic issues have been generally evaluated by considering total SC costs while ecological concerns have been studied as GHG emissions particularly carbon emissions originated from transportation activities. This is not surprising given the high focus on carbon emissions since in many cases; the predominant GHG emitted is CO_2 (Montoya-Torres et al., 2015). Some of the bi-objective models focusing on trade-off between cost and carbon emissions have been presented by (Chibeles-Martins, Pinto-Varela, Barbósa-Póvoa, & Novais, 2012; Diabat and Simchi-Levi, 2009; Harris, Mumford, & Naim, 2014; Pati, Vrat, & Kumar, 2008; Quariguasi Frota Neto et al., 2009; Soysal, Bloemhof-Ruwaard, & van der Vorst, 2014; Wang, Lai, & Shi, 2011). Nevertheless, one of the major drawbacks of this trend is the incapability to control carbon emissions through planning of supply chain networks, since there is no carbon emission constraint involved to delimit carbon emission. A more effective modeling would include carbon cap objective function and carbon emission constraint to delimit carbon emissions.

The second category comprises a larger amount of researches with specific concentration on SC modeling in carbon regulatory schemes. Carbon pricing (also known as carbon taxes) and carbon emissions trading (also known as a cap-and-trade mechanism) are two worldwide adopted carbon regulatory schemes. Emission factors consisting of the carbon tax, carbon trading price and carbon cap play key roles in both of these carbon regulatory schemes. The main criticism of much of the literature in this category is that identifying the optimum answer based on costs does not necessarily mean an optimum alternative for carbon emission.

The carbon pricing scheme aims to control carbon emissions by imposing a tax to the amount of emitted carbon. Some of the bi-objective models have effectively evaluated carbon tax scheme through minimization of cost and carbon emissions, and have started to receive significant interest (Fahimnia, Reisi, Paksoy, & Özceylan, 2013a; Fahimnia, Sarkis, Dehghanian, Banihashemi, & Rahman, 2013b).

The carbon trading scheme allows companies to trade a partial tradable emissions allowances (the cap) among the parties in an economy. Companies violating the maximum allocated carbon allowances are significantly penalized or they could purchase emissions allowances from those emitting less than the maximum allocated carbon allowances (Sarkis, Gonzalez-Torre, & Adenso-Diaz, 2010). Some of the rigorous attempts in a carbon trading scheme can be found in studies by (Diabat et al., 2013; Fahimnia, Sarkis, Choudhary, & Eshragh, 2014). More recent modeling efforts in this context have tried to compare the impact of carbon pricing and carbon trading on SC decisions (Jin, Granda-Marulanda, & Down, 2014; Zakeri, Dehghanian, Fahimnia, & Sarkis, 2015).

The concept of carbon regulatory policy schemes is generally incorporated into models by means of a carbon constraint which imposes a maximum value on carbon emission for entire planning horizon (also known as global carbon constraint). Although the interest in green SC has grown in the last decades, little attention has been paid to carbon emission constraints in modeling of SC networks. The introduction of constraints on carbon emission in SC planning models has been less addressed in literature. We only found the study by Absi, Dauzère-Pérès, Kedad-Sidhoum, Penz, and Rapine (2013) who introduced four different types of carbon emission constraints which could be integrated into production and/or distribution planning. They are: (i) Periodic carbon emission constraint, (ii) Cumulative carbon emission constraint, (iii) Global carbon emission constraint, and (iv) Rolling carbon emission constraint. The function for emission considered as constraint and the upper bound associated with carbon emission (carbon cap) assumed to be given by a regulation.

Carbon policies in many countries are still at the debate stage and how to decide parameters such as carbon cap and constraints require further study (Benjaafar, Li, & Daskin, 2013; Jin et al., 2014). To our knowledge, far too little attention has been paid to a study that focuses on comparing the economic and different carbon emission constraints, particularly a study with a clear focus on distribution planning in JIT contexts. The purpose of this paper is to fill this research gap.

The remainder of the paper is structured as follows: in the next section, the detailed motivations and contributions of this paper are describes. In Sections 4 and Section 5, the problem and the proposed mathematical model are explained respectively. Section 6 presents the solution algorithm. The experimental results, parameter tuning procedure of the algorithm thereafter describes in Section 7. Validation and comparison of the results are presented in Section 8. Managerial insights are discussed in Section 9. The paper ends with concluding remarks and some areas for future research, in Section 10.

3. Motivation and contribution

There are three important areas where this study makes an original contribution:

- In general, to the best of our knowledge, a study that focuses on incorporation of environmental objectives and constraints along with JIT distribution problem is almost spares or even non-existent. In particular, in optimizing carbon emission across green SC (discussed in Section 2.2), there are two primary challenges in developing mathematical models: (1) how to identify a method by which to allocate the initial allowances to the model, and (2) how to select carbon emission constraints so that maximum carbon mitigation can be reached whereas economic performance is not significantly damaged. For first challenge, a number of studies have investigated and proposed some emissions allocation methods (Burtraw, Palmer, Bharvirkar, & Paul, 2001; Böhringer & Lange, 2005; Cramton & Kerr, 2002). In a grandfathering emissions allocation method (Böhringer & Lange, 2005), which is the most commonly applied allocation method, emissions allowances are usually given according to the available historical emission data. But here, we proposed a more accurate method by defining a separate objective in our modeling in order to find the maximum allowed carbon emission. For the second challenge, the carbon emission constraint considered in most papers imposes a maximum value on carbon emissions for entire planning horizon (we refer to it as global carbon constraint). However, in our study, in addition to global carbon constraint, we have analyzed the effect of periodic and cumulative carbon emission constraints, as well.
- Second novelty of this paper is the proposal of an algorithm. As large-scale multi objective MILP problems fail to be solved using exact methods and the cumulative carbon case is an NP-Hard problem (see Appendix A), we propose a hybrid NSGA-II with a novel modified firefly algorithm as local search operator to solve the problem.
  In addition, it should be noted that generally, when metaheuristics algorithms were employed for solve large-scale problems on the subject (Chibeles-Martins et al., 2012; Farahani & Elahipanah, 2008; Ghasimi et al., 2014; Harris et al., 2014) complexity analysis of the considered problems and fine-tuning of the metaheuristics parameters were totally ignored. The proposed solution approach in this research contributes to all these shortcomings. More precisely, an NSGA-II is first employed to provide a set of Pareto solutions. Then, the provided solutions are verified with an NRGA. Then, Taguchi method is considered to tune the parameters of both algorithms. Finally, the proposed novel local search approach named the modified firefly algorithm improves the classical NSGA-II. We show that the proposed approach performs more efficiently compare to classical NSGA-II.
- Finally, analysis of the numerical results provides important managerial implications and policy insights. For policy makers, the findings show the impact of varying the carbon emission cap on total cost and total emission under JIT distribution concept. From managerial perspective, we analyze the relationships between average inventory holding and backlog level per period which can assist mangers to identify critical decisions for planning JIT distributions in a carbon-capped environment.

4. Problem description

The considered network consists of distribution decisions of a three-echelon supply chain with multiple plants, multiple distribution centers, multiple retailers and multiple products using JIT logistics, as shown in Fig. 1.

Mathematical model is formulated to determine two conflicting objectives; minimization of total logistics cost and minimization of maximum allowed carbon quota emission. There are constraints on the holding capacities of the distribution centers' and retailers' storage, and supply capacity. There is also a constraint on amount of emitted carbon which imposed to transportation for distribution of products in the entire logistics network. The carbon emission is proportional to the number of product units shipped and the traveled distance. In addition, there is no inventory at the distributors at the beginning or end of the planning horizon and all deterministic demands have to be satisfied. All parameters and used decision variables are presented in the following. An MILP formulation of the studied problem is also provided.

5. Mathematical model

a. Indices

I	Number of manufacturers
J	Number of distribution centers
K	Number of retailers
P	Number of product types
T	Number of periods
i	Index of manufacturers, $i = 1, 2, \ldots, I$
j	Index of distribution centers, $j = 1, 2, \ldots, J$
k	Index of retailers, $k = 1, 2, \ldots, K$
P	Index of different types of products, $p = 1, 2, \ldots, P$
t	Index of the period, $t = 1, 2, \ldots, T$

b. Parameters

η_{jp}	Unit holding cost of products p at the DC j in each period
η'_{kp}	Unit holding cost of products p at retailer k in each period
υ_p	Unit transportation cost of product p along unit distance
L_{ij}	Distance between manufacturer i and DC j
L'_{jk}	Distance between DC j and retailer k
D_{kpt}	Amount of demand of retailer k for product p at the end period t
Ca_{ipt}	Supply capacity of manufacturer i for product p in period t
Ca'_{jt}	Delivery capacity of DC j in period t
V_{jt}	Total storage (holding capacity) capacity of DC j during period t
U_{kt}	Total storage capacity (holding capacity) of retailer k during period t
S_{kp}	Backlog cost for each product p at retailer k
e	Carbon emission quota per product in grams of carbon per kilometer
E_t	Total carbon emission per period

c. Decision variables

X_{ijpt}	Amount of products p transported from manufacturer i to distributor j during period t
Y_{jkpt}	Amount of products p transported from DC j to retailer k during period t
I_{pjt}	Inventory of product p at DC j at the end of period t
J_{pkt}	Inventory of product p at retailer k at the end of period t
B_{pkt}	Backlog amount of product p at retailer k in period t
$E^{\max}$	Maximum carbon quota allowed per period

Based on the above notations, the following equations are used to formulate the proposed model.

$$MinZ_1 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}(\upsilon_p L_{ij})X_{ijpt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T}\left(\upsilon_p L'_{jk}\right)Y_{jkpt} + \sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t'=1}^{t}\eta_{jp}I_{jpt'} + \sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t'=1}^{t}\eta'_{kp}J_{kpt'} + \sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t'=1}^{t}S_{kp}B_{kpt'} \tag{1}$$

$$MinZ_2 = E^{\max} \tag{2}$$

Subject to

$$E_t = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P} eL_{ij}X_{ijpt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} eL_{jk}Y_{jkpt} \quad \forall t = 1,\ldots,T \tag{3}$$

$$\sum_{j=1}^{J} X_{ijpt} \leqslant Ca_{ipt} \quad \forall i,p,t \tag{4}$$

$$\sum_{k=1}^{K}\sum_{p=1}^{P} Y_{jkpt} \leqslant Ca'_{jt} \quad \forall j,t \tag{5}$$

$$I_{jp(t-1)} + \sum_{i=1}^{I} X_{ijpt} = \sum_{k=1}^{K} Y_{jkpt} + I_{jpt} \quad \forall j,p,t \tag{6}$$

$$\sum_{j=1}^{J} Y_{jkpt} + J_{kp(t-1)} - B_{kp(t-1)} = D_{kpt} + J_{kpt} - B_{kpt} \quad \forall k,p,t \tag{7}$$

$$\sum_{p=1}^{P} I_{jpt} \leqslant V_{jt} \quad \forall j,t \tag{8}$$

$$\sum_{p=1}^{P} J_{kpt} \leqslant U_{kt} \quad \forall k,t \tag{9}$$

$$X_{ijpt}, Y_{jkpt}, I_{jpt}, J_{kpt}, B_{kpt} \geqslant 0, \quad Integer \quad \forall i,j,k,p,t \tag{10}$$

Eq. (1) denotes the first objective function that minimizes the total costs, including transportation costs from the manufacturers to the distributors and from distributors to retailers, costs of holding in both distributors and retailers and penalty costs for amount of backorders at retailers. Note that the transportation costs considered as proportional to the traveling distances. Eq. (2) indicates the second objective function and it minimizes the maximum carbon quota allowed per period. Constraint (3) calculates total carbon emission per period. Constraint (4) considers that total products transported from each manufacturer to all the distribution centers in each period do not exceed the supply capacity of that manufacturer. Constraint (5) indicates the limitations of delivery capacity for the distribution centers. Constraint (6) and Constraint (7) model the flow conservation at distribution centers and retailers level respectively and ensure the JIT delivery. Constraints (8) and (9) show the storage capacity limitation of distributors and retailers respectively. Finally, Constraint (10) ensures non-negativity values of decision variables. We add to this formulation the carbon emission constraint (11), (12) or (13), introduced in the following sections.

i. Periodic carbon emission constraint

This constraint is very tight, and assumes that the amount of carbon emission that is not used in a given period is lost. This constraint is useful if the company must ensure that it meets periodically its carbon emission objectives, and can be formulated as follows:

$$E_t \leqslant E^{\max} \quad \forall t = 1,\ldots,T \tag{11}$$

This constraint forces the average amount of carbon emission at any period t to be lower than or equal than the maximum unitary environmental impact allowed.

ii. Cumulative carbon emission constraint

In constraints (12), if total carbon emission does not exceed an emission cap, the constraint allows the system to save the carbon which is not emitted for a given planning period and use it in subsequent periods not more than the cumulative capacities.

$$\sum_{t'=1}^{t} E_{t'} \leqslant t \times E^{\max} \quad \forall t = 1,\ldots,T \tag{12}$$

iii. Global carbon emission constraint

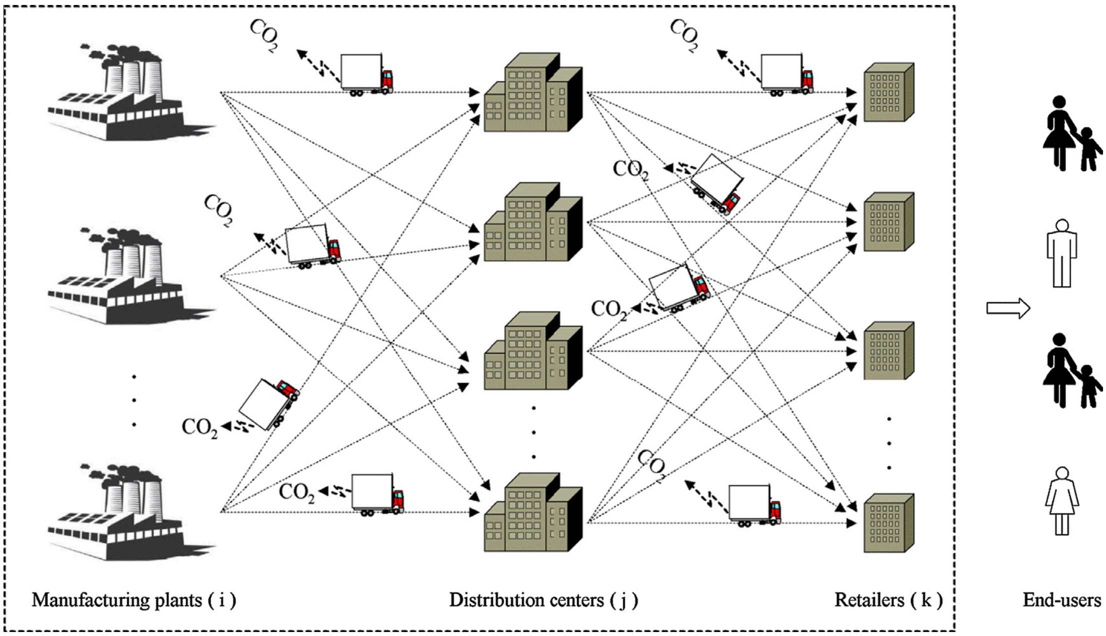

Fig. 1. General scheme of the considered supply chain.

In Constraint (13), the unitary carbon emission over the whole horizon cannot be larger than the maximum unitary environmental impact allowed.

$$\sum_{t=1}^{T} E_t \leqslant T \times E^{\max} \tag{13}$$

The objective functions are in conflict; this means that the value of one of them cannot further improve unless worsening the other. This is shown in Fig. 2.

6. The solution approach

The performed bi-objective mixed integer linear problem in Section 5 especially in its large-scale form requires a large number of repeated evaluations for each of the objective functions to obtain a set of trade-off solutions. Exact methods fail to solve large-size problems of the resulting multi-objective mixed-integer linear programming (Talbi, 2009). In addition, considering cumulative carbon emission constraints has been shown to be an NP-Hard problem (see Appendix A).

This justifies the use of an efficient meta-heuristic algorithm. In the next section, the well-known multi-objective evolutionary algorithm (MOEA) of NSGA-II is presented to obtain a near optimal Pareto front. As there is no available benchmark to evaluate the capability of the proposed algorithm, a well-known NRGA is implemented for verification. In addition, the parameters of both algorithms are tuned by the Taguchi method (Taguchi, Clausing, & Watanabe, 1987). For further quality improvement of obtained solutions, a modified firefly algorithm as local search approach improves NSGA-II.

6.1. NSGA-II

NSGA-II, introduced by Deb, Agrawal, Pratap, and Meyarivan (2000), is one of the frequently used and most applicable techniques in many multi objective optimization problems and it is recognized as one of the best techniques to generate Pareto frontiers. To begin NSGA-II, an initial random population with size N_p chromosomes (solutions) is generated. Next, by using an evaluation function, the objective values of a population are evaluated during several consecutive generations. Then, the population is ranked based on the non-domination sorting procedure in order to present several Pareto fronts of non-dominated solutions. Individuals in the population under evaluation obtain a rank with respect to their non-domination level, where rank 1 is the best level, rank 2 is the next best level and so on, where the individuals with the smallest rank present the first front, the individuals with the second rank covers the second front, and so on. Afterward, the crowding distance is calculated by a linear distance criterion for each front member. In the next step, binary tournament selection operator based on a crowded-comparison operator is applied in order to select two members among the population. The member with the larger crowding distance is chosen if they have an equal rank. Otherwise, the member with lower rank is selected. Then, a new offspring population with size n using selection, crossover and mutation operators is generated to create a population consisting of both current and the new population with size of $(N_p + n)$. To end, the new population members are sorted and a population with an exact size of N_p is selected. Note that solutions are sorted twice in this procedure, first with respect to their crowding distances in the descending order, and second with respect to their

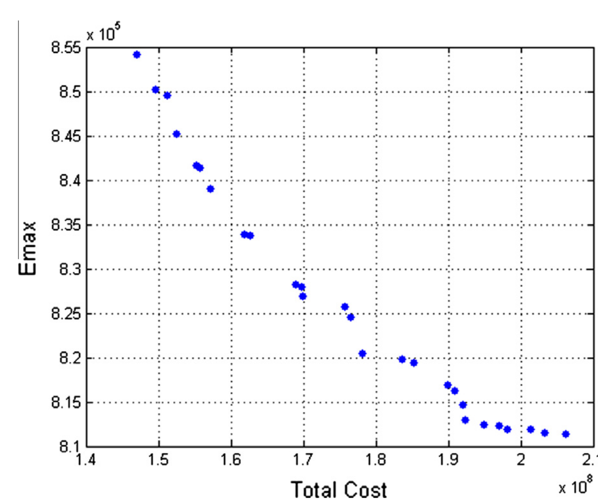

Fig. 2. Relationship between objective functions.

ranks in the ascending order. The new population is used to generate the next new offspring by repeating the above steps. This process is repeated until the stopping condition is met. Finally, a set of non-dominated Pareto-optimal solutions are obtained, as all the solutions are the best in a sense of multi-objective optimization.

In this paper, in order to stop the algorithm, a fixed number of generations determined by the Taguchi method presented in Section 7 are used. In addition, the death penalty approach is used to penalize infeasible solutions that do not satisfy the constraints. For more details on the implementation of NSGA-II refer to Deb et al. (2000) and Deb (2001).

6.2. NRGA

Since there is no benchmark available in the literature in order to verify and validate the solutions obtained by NSGA-II, another popular MOEA called non-dominated ranking genetic algorithm (NRGA) is developed to obtain Pareto fronts.

NRGA was introduced by Al Jadaan (2008) and works similar to NSGA-II, with the exception of exchanging the selection strategy of NSGA-II from the tournament selection to the roulette wheel. More specifically, NRGA combines a ranked-based roulette wheel selection operator with a Pareto-based population-ranking algorithm, in which one of the fronts is first selected by applying the based roulette wheel selection operator. Then, one solution within the candidate front is selected by the same procedure. Therefore, the solutions belonging to the best non-dominated set of the first front have the largest probability of being chosen, as the solutions within a set of the second front are selected with less probability and so on. A similar procedure as the one proposed for the NSGA-II algorithm is employed in this research to stop the NRGA algorithm. In addition, like in the NSGA-II algorithm, infeasible solutions are penalized using the death penalty approach.

6.3. Genetic Operators for GA-based Algorithms

i. Generating first population

With respect to the model constraints, the probability of a randomly produced chromosome being feasible is very low. Thus, some assumptions should be considered in generating the first population chromosomes to achieve the highest possible chance of feasibility. In the proposed mathematical model, variables X_{ijpt} and Y_{jkpt} have direct and indirect relations to the variables I_{jpt}, J_{kpt} and B_{kpt}. Thus, any changes in both of variables X_{ijpt} and Y_{jkpt} lead to certain changes in other variables, consequently these variables were chosen as chromosome. A certain number of chromosomes were randomly created according to:

$$\sum_{j=1}^{J}\sum_{t=1}^{T} Y_{jkpt} = \sum_{t=1}^{T} D_{kpt} \quad \forall k, p \tag{14}$$

$$\sum_{k=1}^{K}\sum_{p=1}^{P} Y_{jkpt} \leqslant Ca'_{jt} \quad \forall j, t \tag{5}$$

Next, the following constraints were used to generate the amount of variable X_{ijpt} randomly:

$$\sum_{i=1}^{I}\sum_{t=1}^{T} X_{ijpt} = \sum_{j=1}^{J}\sum_{t=1}^{T} Y_{jkpt} \quad \forall j, p \tag{15}$$

$$\sum_{j=1}^{J} X_{ijpt} \leqslant Ca_{ipt} \quad \forall i, p, t \tag{4}$$

Fig. 3 displays the graphical representation of the chromosome:

ii. Crossover operators

Crossover operator generates a new solution space as well as providing the opportunity of finding new solutions (offspring) over mating pairs of chromosomes. In this study, in order to prevent permutation, three different both single-point and double-point crossover were considered for mating pairs of chromosomes. These procedures display graphically in Fig. 4 where they were selected randomly with equal probability.

iii. Mutation operator

A mutation operator is applied to improve the diversity of the current population to the new population to explore new solution spaces. Indeed, adding diversity into current population is one of the evolution principles that enhance the algorithm to find better final solutions. Applying mutation operator, a few genes of a candidate chromosome are randomly selected to change their values based on a pre-determined mutation probability of *Pm*. Fig. 5 shows a graphical representation of the mutation operator.

6.4. The Need for Further Improvement of NSGA-II: Hybridization

Presently, upon solving a problem, the main objective is actually to find the best achievable way in solving, rather than promoting a certain metaheuristic. Hybridization is an alternative to improve meta-heuristics. This means that deciding on a sufficient combination of complementary algorithmic concepts could be the key for achieving top performance in solving many hard optimization problems (Blum, Puchinger, Raidl, & Roli, 2011). Adding a local searcher into evolutionary algorithms, sometime known as memetic algorithms, has shown to be successful (see Blum et al., 2011; Boussaïd, Lepagnot, & Siarry, 2013; Lozano & García-Martínez, 2010; Sadeghi, Mousavi, Niaki, & Sadeghi, 2014).

Population-based and single-solution based meta-heuristics are the main categories in mathematical optimization to find a good solution to a problem. As there is a lack of study on the use of recently developed metaheuristics such as firefly algorithm (FA) as a local searcher in the area of supply chain (Griffis, Bell, & Closs, 2012; Zhang et al., 2015), in the next subsection, a modified FA is employed as a local searcher to make the NSGA-II more effective and efficient in finding near-optimum solutions. To see the advantages of the FA over GA and PSO refer to (Yang, 2009).

6.5. A local search operator: a Modified Firefly Algorithm (MFA)

A wonderful sight in the summer night sky of tropical region is flashing light of fireflies. These lights are the main characteristic of fireflies that have two main functions: to warn off potential predators and to attract mating partners. On the other hand, the flashing lights follow more physical rules, i.e., according to the term $I \propto I/r^2$, the intensity of flashing lights I decrease while the distance r increases. This nature-inspired phenomenon motivated Yang (2008) to formulate the firefly algorithm (FA). For more details on the implementation of FA refer to (Yang, 2009).

Experimental results confirm the multi-modal characteristics of FA. This means that classical FA has the ability to find more optimal solutions in the search space. However, it could fall either in premature convergence (trap into the local minimum) or the solutions

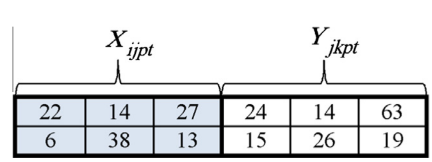

Fig. 3. Chromosome representation.

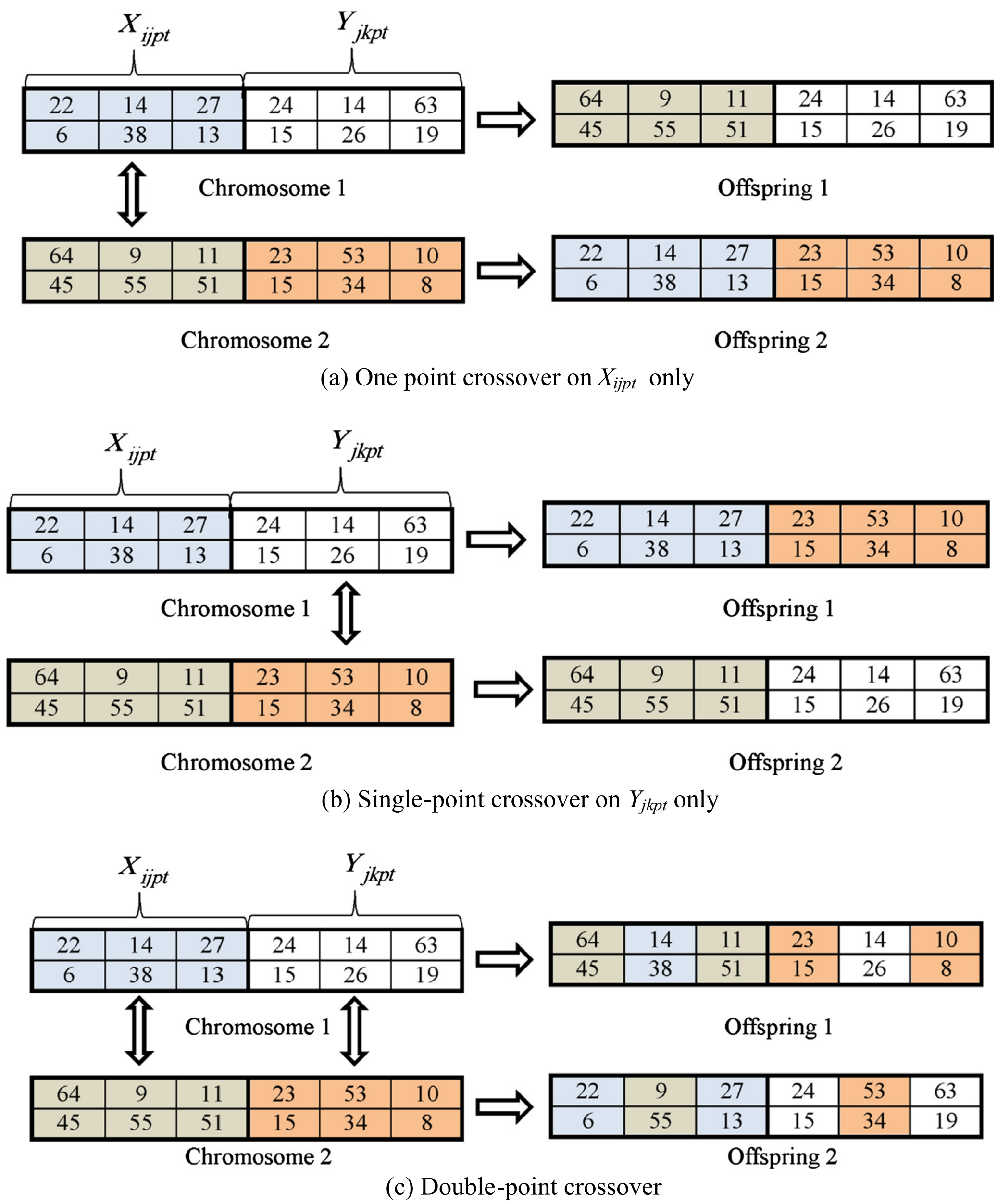

Fig. 4. Crossover representation.

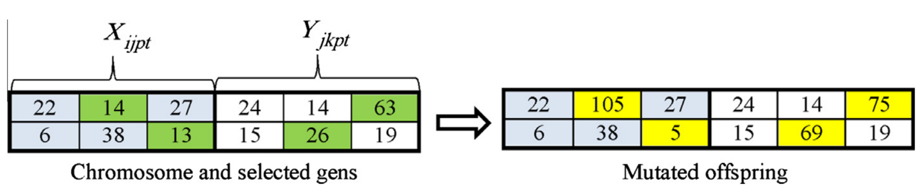

Fig. 5. Display of the mutation operator.

are no longer enhanced (stagnate) in searching space. Apparently, both trends could be linked with the exploration and exploitation components of a process space. Crepinsek, Mernik, and Liu (2011) and Fister, Yang, Brest, and Fister (2013) stated too much exploration slows down the convergence, while too much exploitation causes premature convergence. Various techniques could be applied to prevent premature convergence and also stagnation. For instance, Abdullah, Deris, Mohamad, and Hashim (2012) proposed an explicit balancing procedure for exploration and exploitation by sorting and dividing the initial solutions of FA in two equal groups. They showed neighborhood searching of second group and merging them into the first group of solutions could effectively improve the performance of classical FA, especially premature convergence, stagnation and computation time. In this study, we modified the classical FA in a similar way in order to balance exploration and exploitation to avoid premature convergence and stagnation by using additional operators into classical FA. We ranked and sorted the initial solutions of FA into two equal groups, after that, the operators, namely swap, reversion, and insertion (Fig. 7) are applied in the second groups in order to neighborhood search of the solutions, where these operators are selected randomly. Then, the obtained solutions merged to the first group and FA has been applied for the new potential solutions.

These operators first generate a random neighbor *sol′* for initial solution sol in second group. Then, their cost functions denoted by $f(sol')$ are obtained. If $f(sol')$ is better than the $f(sol)$ (fitness function of first group), *sol′* is accepted as a new solution, and is replaced with *sol*; otherwise, the previous best solution remains in the potential solutions in second group. Finally, the new obtained solutions merged with those are in first group and FA is run to obtain the best solutions. Note that the parameters of the FA are set by a trial and error method in this paper. A graphical representation of MFA can be seen in Fig. 6.

$$\begin{bmatrix} 63 & \underline{12} & 33 & 48 & \underline{9} \end{bmatrix} \xrightarrow{\text{Swap}} \begin{bmatrix} 63 & 9 & 33 & 48 & 12 \end{bmatrix}$$
$$\begin{bmatrix} 63 & \underline{12 \;\; 33 \;\; 48 \;\; 9} \end{bmatrix} \xrightarrow{\text{Reversion}} \begin{bmatrix} 63 & 9 & 48 & 33 & 12 \end{bmatrix}$$
$$\begin{bmatrix} 63 & \underline{12} & 33 & 48 & \underline{9} \end{bmatrix} \xrightarrow{\text{Inversion}} \begin{bmatrix} 63 & 33 & 48 & 9 & 12 \end{bmatrix}$$

Fig. 7. Additional operators in modified FA.

7. Experimental results

7.1. Test problems

To illustrate the verification and the applicability of the proposed model, some test problems with different sizes were extracted from the similar study in literature (Farahani &

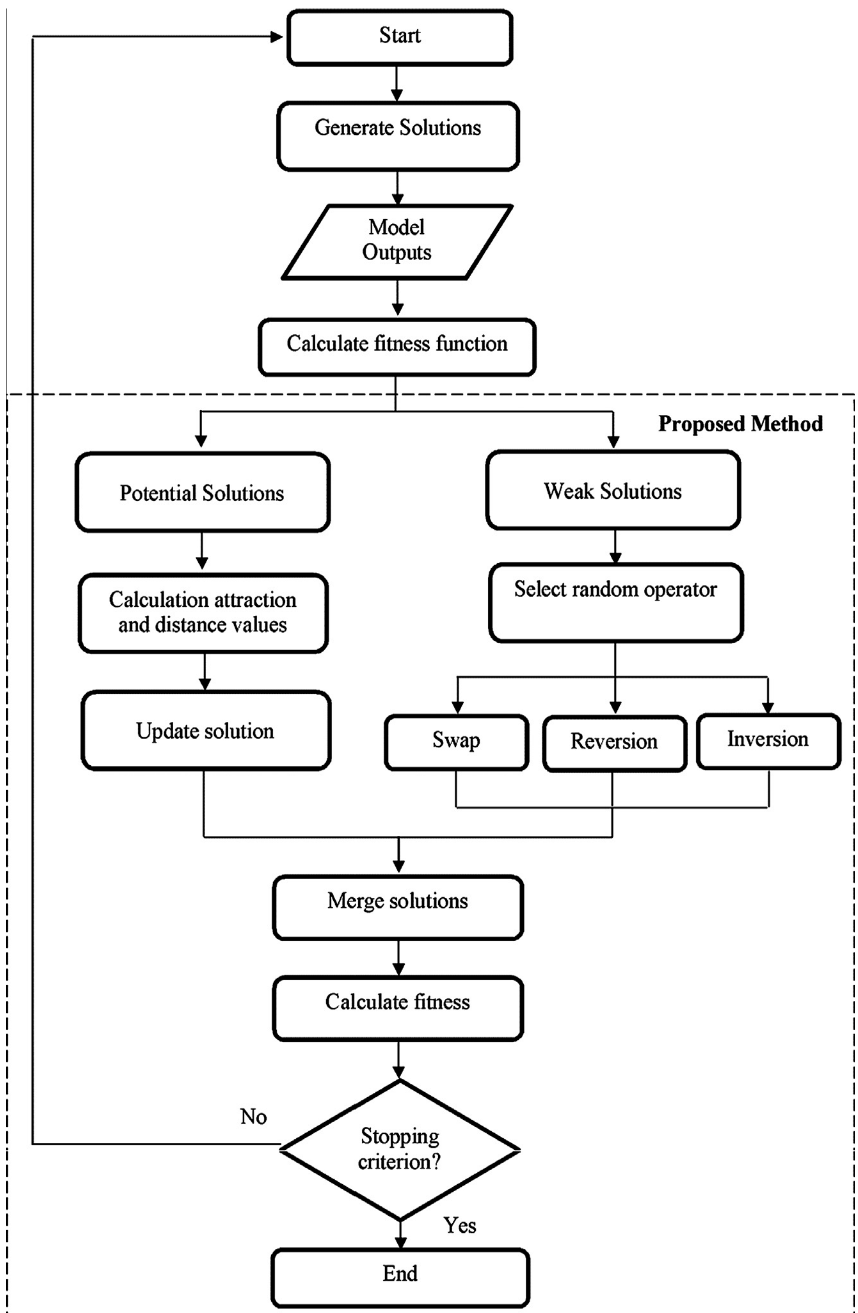

Fig. 6. Graphical representation of modified FA.

Table 1
Test problems size.

Problem size	Problem code	No. of plants (I)	No. of DCs (J)	No. of retailers (K)	No. of products (P)	No. of periods (T)
Small	S1	2	2	4	2	6
	S2	2	2	15	2	6
Medium	M1	3	5	10	2	12
	M2	2	8	15	4	6
Large	L1	3	10	20	2	12
	L2	6	12	25	8	12
	L3	8	15	40	8	12

Elahipanah, 2008). Seven problems with different sizes of small, medium, and large were designed to simulate different near real-world cases. The values of parameters for every problem are generated randomly based on uniform distribution between their lower and upper bounds. The provided test problems and their values are presented in Tables 1 and 2.

7.2. Parameter tuning

In implementing of meta-heuristic algorithms, the obtained results are sensitive to algorithms parameters. Therefore, the parameters require being fine-tuned calibrating in order to obtain solutions with better quality (fitness function value). Fisher (1935) studied design of experiments (DOE) called factorial designs to examine the impact of several factors on the mean of a response. Later, Taguchi introduced fractional factorial experiments (FFEs) which reduced large number of experiments in the full factorial designs (Taguchi et al., 1987). In the Taguchi method, there are two affecting factors: noise factors N and controllable factors S, where only S can be directly controlled in the experiments. To analyze the obtained results by the Taguchi method, there are two suggestions in the literature. The first suggestion is to use the analysis of variance for the experiments that are repeated once. Second, to apply the signal to noise ratio (S/N) as the response variable for the experiments that have multiple runs, where S represents controllable factors and N shows noise factors affecting the response (Roy 1990). Since the meta-heuristics are run several times to obtain a better solution, in this research we use S/N to analyze the solutions. For more information regarding the Taguchi method see (Taguchi, Chowdhury, & Wu, 2005).

7.2.1. Taguchi method implementation

The Taguchi method includes five steps. First, parameters with major influences on the response are determined. Second, to implement the experiments a trial and error procedure determines the values of the parameters that provide good fitness function (mainly because Taguchi emphasized that quality should be designed at the beginning of production and not during it). Third, a suitable orthogonal array is selected with respect to available degrees of freedom (DOF). In this regard, the smallest orthogonal array corresponding to DOF should be chosen to minimize experimentation time. Fourth, the obtained design is used to implement the experiments. Finally, the results are analyzed based on the S/N approach. The parameters of both the NSGA-II and the NRGA algorithms along with their levels are shown in Table 3. The Taguchi L^9 orthogonal array is utilized to run the experiments and tune the parameters (See Table 4).

Four different responses, each presenting a specific quality of a solution obtained by a MOEA, are determined for the experiments. They are (1) number of Pareto solutions (NPS), Generational distance of a solution (GD), spacing (Sp), and the best solution obtained (Best_Sol) (Deb 2001). Note that in order to obtain the Best_Sol, the fitness values of the solution for the two objective

Table 2
Values of parameter range in test problems.

Parameter	Value	Unit
η	[100–300]	Unit of money
η'	[100–250]	Unit of money
υ	[50–100]	Unit of money
L	[200–450]	Kilometer
L'	[200–450]	Kilometer
D	[50–100]	Unit of product
Ca	[400,400 + 160*K/I]	Unit of product
Ca'	[70,70 + 160*P*K/J]	Unit of product
V	[500–700]	Unit of product
U	[100–200]	Unit of product
S	[800–1000]	Unit of money
e	0.3	Kilogram per kilometer per product

functions are first normalized into a uniform and dimension-less scale (Eq. (16)) (Deb 2001). Then, they are summed together with a weight of 0.5 each. The solution with the lowest combined value of the normalized objective function values is selected as the best. Note that since the problem is minimization, Best_Sol, GD and Sp with lower values explain better efficiency of MOEAs. On the other hand, NPS with bigger values explain the better efficiency of MOEAs.

$$\begin{cases} TC \to TC/10^{(\text{number of degits of TC}-2)} \\ E^{\max} \to E^{\max}/10^{(\text{number of degits of } E^{\max}-2)} \end{cases} \tag{16}$$

Regarding the provided test problems in Table 2, a numerical example for problem "M1" and each parameter level of the L^9 from orthogonal arrays, each problem is run five times. Table 5 shows the results obtained based on an arbitrary run. The sums of the obtained metrics of the five runs using the NSGA-II algorithm are normalized in Table 5. These normalized values are used in the Taguchi method as the response values of experiments based on different combinations of the parameter levels. Since a solution with the highest Sum is desired, the aim is to find maximum S/N calculated by

$$S/N = -10log\left(\frac{1}{n}\sum_{i=1}^{n} Sum_i^2\right) \tag{17}$$

where $Sum_i = 1, \ldots, 5$ is the response in ith replication of the Taguchi method and $n = 5$ is the number of replications in experiments.

Tables 6 and 7 show the experimental results of NSGA-II and NRGA under different scenarios of the parameter combinations, respectively where "1", "2", and "3" refer to the first, the second, and the third level of the parameters. Regarding Eq. (17), these tables present S/Ns as well. In addition, it can be seen from Figs. 8 and 9 that the highest mean of S/N plot for different levels of the NSGA-II and NRGA parameters is the best. Therefore, Table 8 contains the optimal parameter values of the algorithms. It should be noted that Np and It both depend on the problem size. Note also that Minitab 16.2.4.0 is used to employ the Taguchi method.

Table 3
NSGA-II and NRGA parameters.

Variable	Level (value)		
	1	2	3
It	100	125	150
Np	70	75	80
Pc	0.6	0.7	0.8
Pm	0.1	0.2	0.3

Table 4
The metrics obtained by NSGA-II.

Sp	*GD*	*NPS*	*Best_Sol*
8569.8686	38.2941	6	18.2951
4609.1188	29.1420	16	18.1211
3418.3745	26.5164	16	18.2391
851.8200	19.4006	54	18.1677
5021.0510	11.4645	14	17.5671
3190.9401	14.8014	31	17.6695
353.8822	13.6785	70	18.0130
1870.8734	24.7202	66	18.0793
2128.9067	10.9382	26	17.5044

Table 5
Normalized metrics obtained by NSGA-II.

Sp	*GD*	*NPS*	*Best_Sol*	*Sum*
0.0413	0.2856	0.0857	0.9568	1.3694
0.0768	0.3753	0.2286	0.9660	1.6467
0.1035	0.4125	0.2286	0.9597	1.7043
0.4154	0.5638	0.7714	0.9635	2.7142
0.0705	0.9541	0.2000	0.9964	2.2210
0.1109	0.7390	0.4429	0.9907	2.2834
1.0000	0.7997	1.0000	0.9718	3.7714
0.1892	0.4425	0.9429	0.9682	2.5427
0.1662	1.0000	0.3714	1.0000	2.5377

Table 6
Experimental results of NSGA-II.

It	*Np*	*Pc*	*Pm*	Sum_1	Sum_2	Sum_3	Sum_4	Sum_5	*S/N*
1	1	1	1	1.3694	1.7496	1.8009	1.4213	1.2646	3.3939
1	2	2	2	1.6467	1.8973	1.4919	1.3905	1.4440	3.7826
1	3	3	3	1.7043	1.4830	1.3692	2.7894	1.2602	3.7869
2	1	2	3	2.7142	3.1417	2.9995	2.1567	1.4493	6.8222
2	2	3	1	2.2210	1.8921	1.6175	2.2042	1.3672	4.9346
2	3	1	2	2.2834	1.5485	2.4075	1.5298	1.4759	4.7684
3	1	3	2	3.7714	3.9935	2.5019	3.1585	2.3358	9.3833
3	2	1	3	2.5427	1.6309	3.0957	2.6404	2.2050	7.0594
3	3	2	1	2.5377	2.4316	2.5197	2.0325	3.9966	8.0321

Table 7
Experimental results of NRGA.

It	*Np*	*Pc*	*Pm*	Sum_1	Sum_2	Sum_3	Sum_4	Sum_5	*S/N*
1	1	1	1	1.5368	1.9415	1.2673	1.2563	1.5043	3.2114
1	2	2	2	2.0335	1.8516	1.9890	1.1916	1.8371	4.4688
1	3	3	3	1.1265	1.2469	1.3208	1.5989	1.4704	2.4289
2	1	2	3	2.0393	2.2424	2.1744	1.9965	1.9595	6.3371
2	2	3	1	1.5547	1.2672	1.3265	1.6601	1.3862	3.0311
2	3	1	2	1.9334	1.8883	1.3477	2.6924	1.9251	5.2105
3	1	3	2	2.1471	1.9424	1.9117	2.3470	1.9920	6.2372
3	2	1	3	1.9132	2.1659	2.1419	2.1909	2.1027	6.4250
3	3	2	1	2.1191	2.7507	2.7708	2.6937	1.6799	7.0896

8. Comparative study

In this section, the performance of NSGA-II is compared with the one of NRGA in order to verify and validate the obtained results by NSGA-II. To do so, each problem is run 10 times, where the best run is selected for comparison which is obtained by the simple additive weighting approach of multi-attribute decision-making processes with equal weight of criteria. Moreover, the CPU time and the set coverage, Q(A, B) metrics are also applied to evaluate the performances of both algorithms, where the set coverage metric compares the Pareto optimal solutions (A, B) based on the concept of dominance relations (Deb 2001). Therefore, these metrics together with those defined in the previous section are used to compare NSGA-II and NRGA. Table 9 shows the obtained results of these six metrics for both algorithms where NSGA-II performs better that NRGA in terms of the majority of metrics. Based on the results in Table 9, majority of Pareto solutions obtained by NRGA are dominated by NSGA-II. In addition, a quality criterion, the percentage of error, is defined to show the percentage of deviation of the *Best_Sol* values of the NSGA-II solutions from the *Best_Sol* values of NRGA on average, according to the following equation:

$$\%error = \frac{(NRGA.BestSol - NSGAII.BestSol)}{NSGAII.BestSol} \times 100 \tag{18}$$

The results for the *%error* metric shows that the Pareto optimal solutions obtained by NSGA-II in periodic, cumulative and global carbon constraint cases have enough competency, with only less than 0.05%, 0.54% and 2.53% differences on average respectively compared with NRGA.

Note that throughout this paper all calculations are performed on a PC with Intel core (TM) i5-CPU 2.50 GHz, RAM 4.00 GB. Moreover, the algorithms were coded using MATLAB 2010b software.

8.1. Improved results

Considering modified firefly algorithm (MFA) as a local search operator, the proposed algorithm, NSGA-II, explained in Section 6, is improved to optimize the bi-objective model presented in Section 5. This algorithm is hereafter referred to as hybrid NSGA-II. Since MFA is able to discover more Pareto dominant solutions in the search space, as the local search based method can obtain more feasible solutions. The results presented in Table 10 illustrate that MFA makes the hybrid algorithms more efficient in terms of all the performance metrics particularly for obtained solutions quality and CPU time. The results shows that the obtained solutions by hybrid NSGA-II (*Best_Sol*) are less than that of the non-hybrid algorithm by 5.14% on average for different sizes of problem with different carbon constraints. In addition, the results of considering MFA as a local search operator presented in Table 10 illustrate that MFA makes the hybrid NSGA-II faster compared to classical NSGA-II in terms of the required CPU time by reducing 6.62% of CPU time on average for different sizes of problem with different carbon constraints. Fig. 10 confirms these claims. It can be concluded, the hybrid NSGA-II becomes more efficient using the local search operator, since they have similar cores to that of the non-hybrid algorithm, the former algorithm performs better than the latter.

9. Managerial insights

9.1. Analysis of total cost and total emission

Seven instances of the model were solved by combining the three carbon constraints options with the two optimization criteria, cost and carbon cap. In the absence of carbon emission constraint, the decisions in the considered logistic network are made to minimize the sum of its transportation costs, holding costs and backlogging cost. In presence of carbon constraint, as expected, reducing the emission cap increases total cost. This can be explained by noting that a tighter cap increase the possibility of

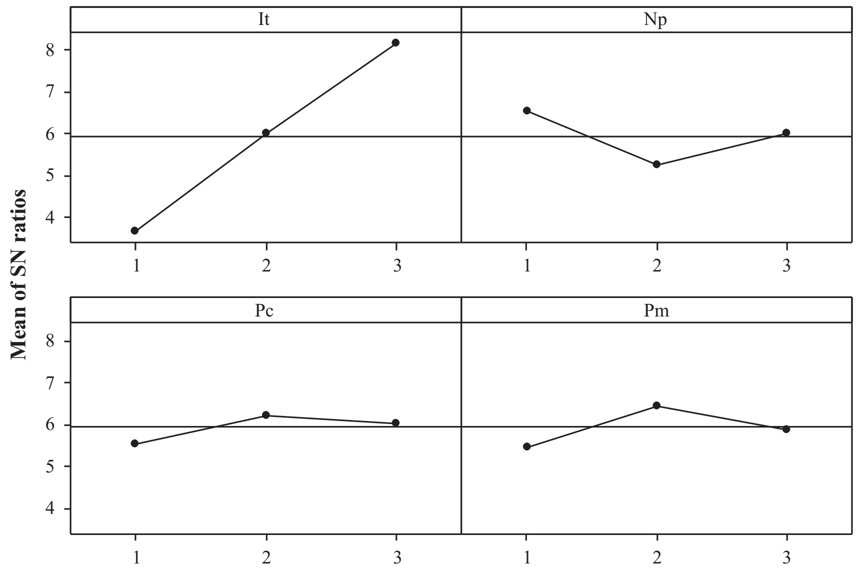

Fig. 8. The mean S/N plot for different levels of the NSGA-II parameters.

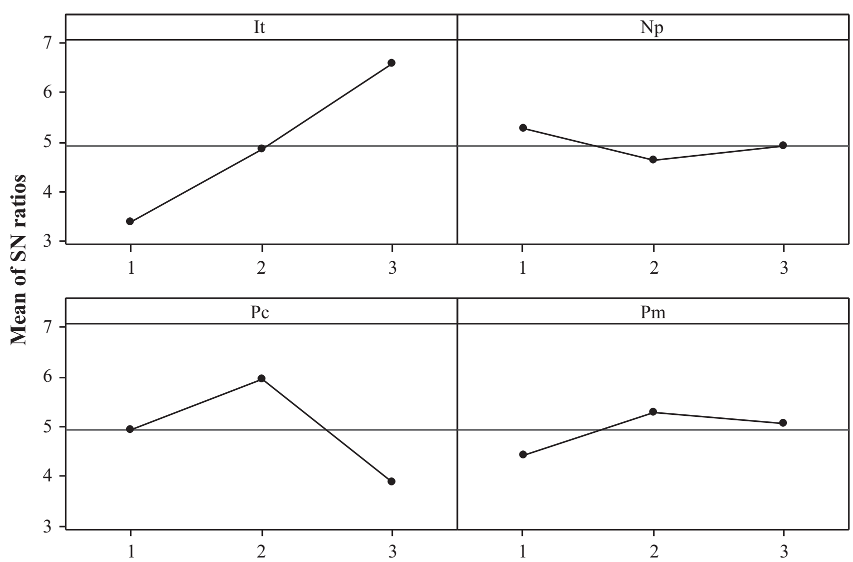

Fig. 9. The mean S/N plot for different levels of the NRGA parameters.

Table 8
Tuned parameters for NSGA-II and NRGA.

NSGA-II	Value	NRGA	Value
It	150	*It*	150
Np	70	*Np*	70
Pc	0.7	*Pc*	0.7
Pm	0.2	*Pm*	0.2

being out of stock at retailers which leads to a higher backlogging cost. In addition, the system tries to hold more inventories in both DCs and retailers in order to prevent backlogs. Consequently, the system ends up with a higher total cost. On the other hand, considering more strict policies such as periodic limitation in carbon emission lead to increase the total cost. Fig. 11 shows the impact of varying the emission cap on total cost (for problem L3) when different carbon constraints are imposed. The findings from modeling results and Fig. 11 show that considering more flexible constraints (policies) provide a smaller cost under the same emission target.

Fig. 12 summarizes the difference among the three constraints regarding their sensitivity, which provides some insights for policy makers. Surprisingly, lower emission caps in JIT-logistics lead to higher total emissions and tighter caps can paradoxically end up with greater total emissions. This is due to the fact, that imposing tighter carbon cap and more strict policies increase the possibility of being out of stock at retailers. To fulfill demands and provide lower backlog level, the system requires shipping the products at maximum possible level. Carrying more products in a period caused to higher emission. In fact, one could argue that imposing tighter emission caps especially on more strict polices such as period by period basis removes a company's opportunity to emit more in one period if they can emit significantly less in subsequent periods. For instance, consider a setting with relatively high fixed emissions (i.e. emissions related to frequent transportation in JIT distribution). In such situation, overall emissions of a company

Table 9
Comparison of experimental results: NSGA-II vs NRGA.

	Problems	NSGA-II						NRGA					
		Sp	*GD*	*NPS*	*Q(A,B)*	*Best_Sol*	*CPU time*	*Sp*	*GD*	*NPS*	*Q(B,A)*	*Best_Sol*	*CPU time*
Periodic constraint	S1	3652.81	7.03	29	0	8.13	19.79	3641.90	7.01	40	1	8.04	19.23
	S2	2542.53	8.35	38	0.1174	7.73	24.61	2528.53	8.27	40	0.8826	7.58	23.82
	M1	3865.71	8.49	45	1	18.42	35.53	4301.71	8.61	38	0	18.72	35.23
	M2	3357.23	9.09	60	1	29.33	142.91	3407.49	9.54	55	0	29.42	144.08
	L1	2812.79	9.64	81	1	35.92	641.98	2807.91	9.92	78	0	36.08	643.77
	L2	3994.88	8.91	71	1	17.21	949.03	4122.66	9.03	69	0	16.2236	956.54
	L3	3113.90	8.07	78	1	15.66	1129.06	3131.78	8.25	70	0	16.22	1130.12
	Average	3334.26	8.51	57.43	0.7310	18.91	420.42	3420.28	8.66	55.71	0.2689	18.90	421.83
Cumulative constraint	S1	3822.79	7.46	40	0	7.38	17.76	4289.88	7.28	38	1	7.44	18.07
	S2	2451.31	8.14	38	1	6.69	21.05	2492.49	9.23	39	0	7.06	21.36
	M1	4470.96	8.14	49	1	18.83	38.94	4880.98	7.99	42	0	18.96	39.66
	M2	3339.82	9.12	68	0.8234	28.90	138.76	3285.73	9.64	60	0.1766	28.90	150.35
	L1	2533.65	9.52	83	0	34.98	642.17	3282.97	9.07	81	1	35.12	644.84
	L2	3957.91	8.76	74	1	16.20	935.18	4587.90	8.11	66	0	16.20	943.75
	L3	3167.30	7.99	81	1	14.95	1128.56	3415.77	7.18	78	0	14.93	1140.09
	Average	3391.96	8.44	61.85	0.6890	18.27	417.48	3747.95	8.36	57.71	0.3109	18.37	422.58
Global constraint	S1	3375.57	7.27	40	1	7.31	18.43	4706.49	7.33	24	0	8.07	18.41
	S2	2397.14	8.51	37	1	6.54	23.62	2563.99	8.59	37	0	6.43	24.29
	M1	4594.76	8.72	48	1	18.17	35.36	4356.16	8.75	48	0	19.19	35.93
	M2	3137.42	9.25	64	1	30.22	136.93	3337.85	9.30	64	0	30.83	135.35
	L1	2051.27	9.74	80	0.8837	16.08	640.38	2267.02	9.76	80	0.1163	16.13	644.84
	L2	3221.05	8.56	71	1	14.77	932.27	3720.96	8.61	71	0	14.76	940.63
	L3	3052.98	7.70	83	1	14.48	1129.50	3729.35	7.74	83	0	14.94	1129.44
	Average	3118.60	8.54	60.43	0.9833	15.37	416.64	3525.97	8.58	58.14	0.0167	15.76	418.41

Table 10
Comparison of experimental results: NSGA-II vs hybrid NSGA-II.

	Problems	NSGA-II						Hybrid NSGA-II					
		Sp	*GD*	*NPS*	*Q(A,B)*	*Best_Sol*	*CPU time*	*Sp*	*GD*	*NPS*	*Q(B,A)*	*Best_Sol*	*CPU time*
Periodic constraint	S1	3652.81	7.03	29	0.4888	8.13	19.79	3656.43	7.00	40	0.5112	8.07	16.27
	S2	2542.53	8.35	38	0.4952	7.73	24.61	2532.72	8.28	40	0.5048	7.52	22.06
	M1	3865.71	8.49	45	0.3201	18.42	35.53	3860.39	8.41	48	0.6799	18.16	30.95
	M2	3357.23	9.09	60	0.2650	29.33	142.91	3351.08	9.01	63	0.7350	28.10	131.08
	L1	2812.79	9.64	81	0	35.92	641.98	2810.94	9.57	84	1	34.90	629.16
	L2	3994.88	8.91	71	0	17.21	949.03	3992.47	8.86	75	1	16.63	921.77
	L3	3113.90	8.07	78	0	15.66	1129.06	3111.65	8.01	82	1	14.18	1015.27
	Average	3334.26	8.51	57.43	0.2242	18.91	420.42	3330.81	8.45	61.71	0.7758	18.22	395.22
Cumulative constraint	S1	3822.79	7.46	40	0.4064	7.38	17.76	3825.04	7.15	40	0.5936	7.32	16.69
	S2	2451.31	8.14	38	0.3867	6.69	21.05	2444.19	8.02	39	0.6133	5.84	20.33
	M1	4470.96	8.14	49	0	18.83	38.94	4465.38	8.04	51	1	18.53	31.17
	M2	3339.82	9.12	68	0.2236	28.90	138.76	3292.66	8.98	69	0.7764	25.29	130.49
	L1	2533.65	9.52	83	0	34.98	642.17	2307.71	9.03	85	1	31.83	625.25
	L2	3957.91	8.76	74	0	16.20	935.18	3889.23	8.27	79	1	15. 03	916.41
	L3	3167.30	7.99	81	0	14.95	1128.56	3154.95	7.21	85	1	12.92	1009.83
	Average	3391.96	8.44	61.85	0.1453	18.27	417.48	3339.88	8.1	64	0.8547	16.955	392.88
Global constraint	S1	3375.57	7.27	40	0.4463	7.31	18.43	3299.48	7.11	40	0.5537	7.29	14.86
	S2	2397.14	8.51	37	0.3607	6.54	23.62	2302.79	7.97	39	0.6393	6.51	20.51
	M1	4594.76	8.72	48	0	18.17	35.36	4487.12	8.03	51	1	17.98	31.37
	M2	3137.42	9.25	64	0	30.22	136.93	3130.06	8.92	67	1	29.16	121.73
	L1	2051.27	9.74	80	0	16.08	640.38	2011.36	9.09	83	1	15.88	625.45
	L2	3221.05	8.56	71	0	14.77	932.27	3217.85	8.16	74	1	13.81	882.33
	L3	3052.98	7.70	83	0	14.48	1129.50	3001.64	7.14	85	1	13.04	1023.47
	Average	3118.60	8.54	60.43	0.1152	15.37	416.64	3064.33	8.06	62.71	0.8847	14.81	388.53

could be reduced by reducing the orders frequency, while carrying more inventories in certain periods could mean greater carbon emissions in those periods. In fact, emitted carbon during transport inventories might violate emission caps if the companies are imposed on a periodic basis emission limitation. These observations have two important implications. First, companies and policy makers need to be conscious that the specifics of how emission caps are implemented can have very different impacts on tactical costs and total emission. Second, devising policies that enable companies to decide when and how to fulfill the required cap could let firms fulfill these caps at significantly lower costs.

9.2. Analysis of inventory holding and backlog level

The goal of JIT delivery is to distribute products on an as-needed basis. In practice, finding a balance between inventory and backlog levels is a key component in efficient JIT distribution of products (Farahani & Elahipanah, 2008). However, the limitation in carbon emissions for the considered JIT distribution model in this study can potentially limit the number of products to be shipped and consequently influence inventory holding and backlog levels.

To distinguish the sensitivity of inventory and backlog amounts between the "*JIT problem*" (the problem without carbon emission

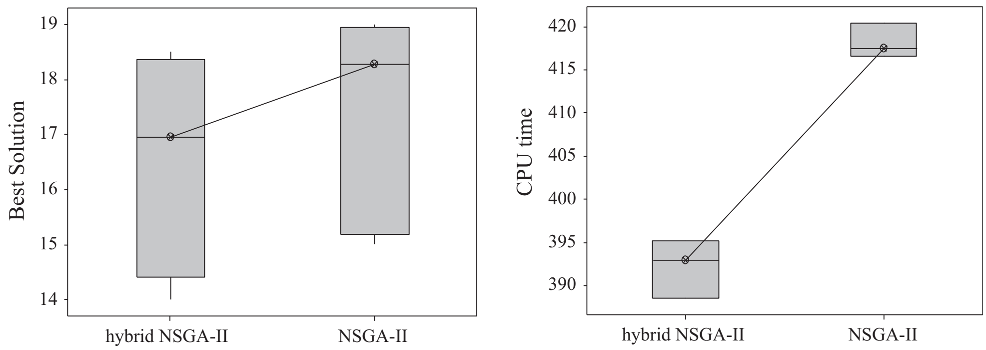

Fig. 10. Boxplot of algorithms comparison in terms of obtained best solution and CPU time.

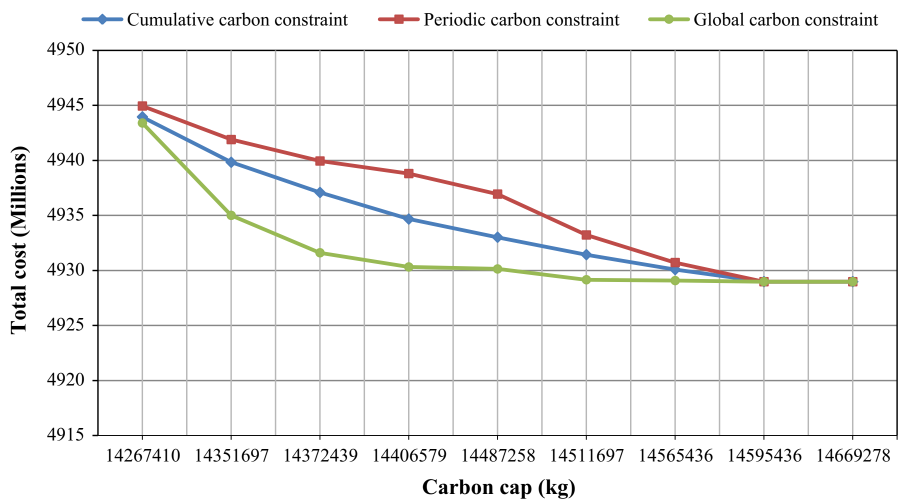

Fig. 11. Carbon cap versus total cost.

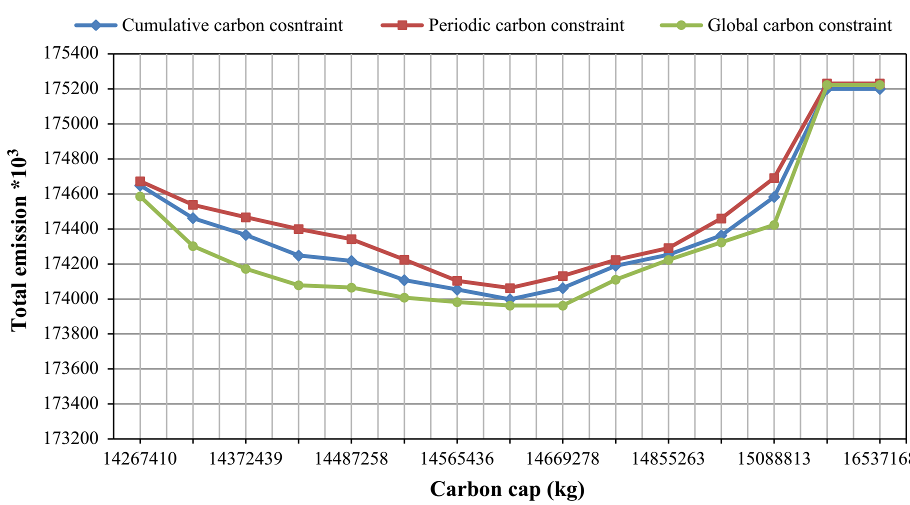

Fig. 12. Carbon cap versus total carbon emission in entire planning horizon.

constraint and carbon cap (E^{max}) considerations) and those under carbon emission considerations (periodic, cumulative and global carbon emission cases), a comparative study was carried out to analyze all cases. For this purpose, the first case ("*JIT problem*") was solved by excluding the carbon objective (E^{max}) and carbon constraint from the model. For the second cases (periodic, cumulative and global), the problems were solved under the same emission target (E^{max}) to provide a meaningful comparison. To do so, the value of the second objective function (E^{max}) of five solutions obtained by hybrid NSGA-II was inserted into the model formulation as a new constraint. Then the model was solved with periodic, cumulative and global constraints. Tables 11 and 12 show the average total products holding (inventory level) per period in DCs and retailers echelons respectively. Table 13 gives details of average

Table 11
Average inventory holding at DCs per period under different carbon cap ($\bar{I}$).

Problem description	Carbon cap (kg) (E^{max})				
	Tighter cap →			**Wider cap**	
	14,267,410	14,372,439	14,487,258	14,565,436	14,669,278
Periodic carbon emission case	1331	1274	1196	1104	1002
Cumulative carbon emission case	1298	1210	1143	1079	991
Global carbon emission case	1297	1202	1136	1061	987
JIT problem (without carbon emission constraint and carbon cap objective)	Average inventory holding amount per period = 916				

Table 12
Average inventory holding at retailers per period under different carbon cap ($\bar{J}$).

Problem description	Carbon cap (kg) (E^{max})				
	Tighter cap →		**Wider cap**		
	14,267,410	14,372,439	14,487,258	14,565,436	14,669,278
Periodic carbon emission case	1015	1001	988	973	957
Cumulative carbon emission case	862	812	791	766	740
Global carbon emission case	854	801	784	758	733
JIT Problem	Average inventory holding amount per period = 663				

Table 13
Average backlog level at retailers per period under different carbon cap ($\bar{B}$).

Problem description	Carbon cap (kg) (E^{max})				
	Tighter cap →		**Wider cap**		
	14,267,410	14,372,439	14,487,258	14,565,436	14,669,278
Periodic carbon emission case	1981	1812	1743	1659	1572
Cumulative carbon emission case	1950	1799	1731	1644	1555
Global carbon emission case	1944	1778	1708	1621	1531
JIT Problem	Average backlog amount per period = 1174				

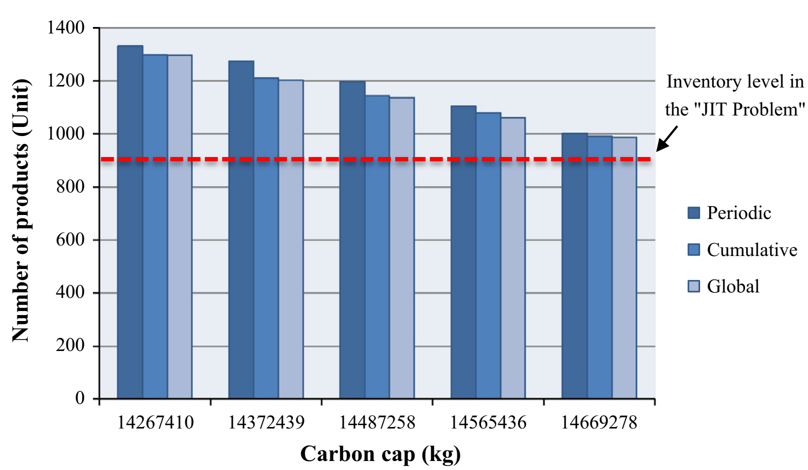

Fig. 13. Carbon cap versus average inventory holding level at DCs' echelon.

overall products backlog amount (backlog level) per period at retailers.

It can be seen from Table 11 (and also Fig. 13) that on average total inventory holding level at DCs echelon increases when the carbon cap becomes tighter. In addition, among all three cases (periodic, cumulative and global carbon emission constraints), the periodic carbon emission case increases the DCs' inventory holding level more than the other two cases. Compared to the situation in which there is no limitation on carbon emissions (*JIT Problem*), managers should be expected to spend more costs for inventory holding. The same observation holds at retailers' echelon according to the Table 12 results (which is depicted in Fig. 14). However, the cumulative and global carbon emission cases (compare to periodic case) may provide more flexibility to retailers, which may enjoy a smaller holding cost increase under the same emission target.

The differences between backlog level in the three cases and the "*JIT problem*" are highlighted in Fig. 15 (and also Table 13).

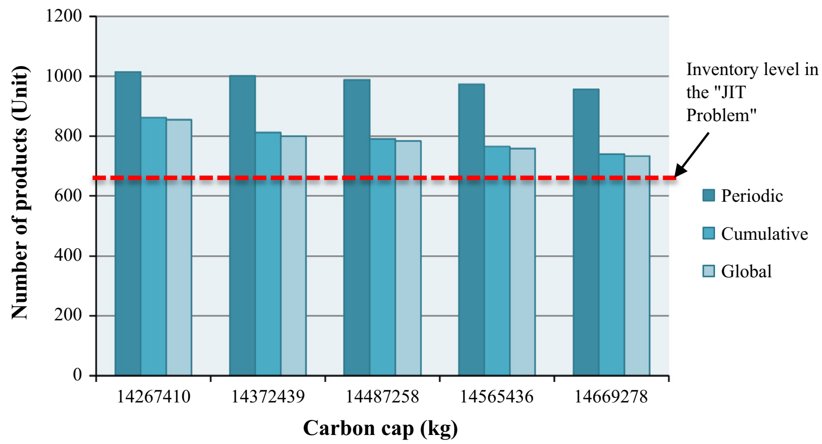

Fig. 14. Carbon cap versus average inventory holding level at retailers' echelon.

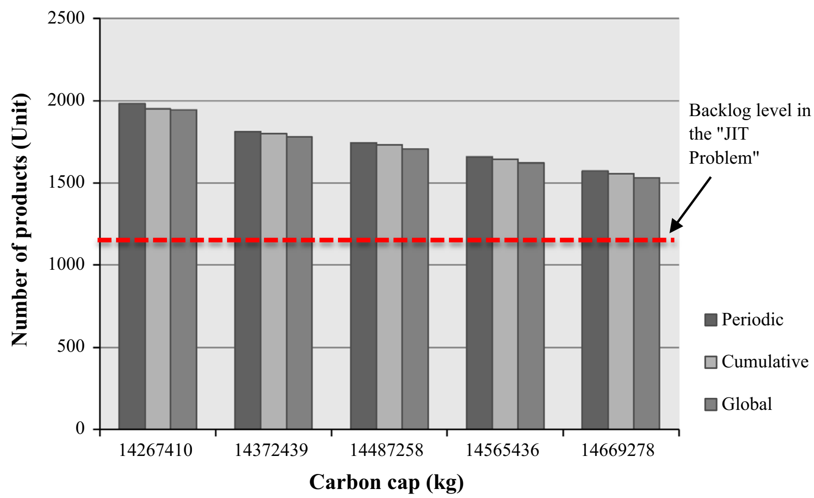

Fig. 15. Carbon cap versus average backlog level at retailers' echelon.

It is apparent from this figure that tighter cap leads to increase backlog level amount at retailers. However, while very few differences exist between average backlog levels for three cases at retailers, a tighter cap leads to higher backlog levels. Compared to the "*JIT problem*", it seems that retailers must expect a higher backlog level under carbon emission limitations, particularly in strict carbon emission cases. Policy makers must be aware that stricter emission policies could result in very challenging conditions for companies.

In summary, the three studied cases have different challenges in inventory and backlog levels in both DCs and retailers. In addition, these results further support the claim that tighter carbon caps as well as stricter carbon emission policies could lead to higher total cost.

10. Conclusion and recommendations for future research

In this study, we developed a new MILP model for a carbon-capped JIT distribution network. The objectives were the minimization of total logistics costs and carbon cap. We investigated the proposed model under three different carbon emission environments by imposing periodic, cumulative and global carbon emission constraints. According to the reviewed literature, this research is probably the first attempt to formulate a JIT distribution network along with environmental considerations.

We also proved that the problem with cumulative carbon constraints is an NP-Hard problem. In order to solve the formulated problem, two well-known multi-objective genetic algorithms, namely NSGA-II and NRGA were tuned using Taguchi method first. Then, their performances were compared in terms of six multi-objective performance metrics. For further improvement of the results obtained by NSGA-II, a novel modified FA was proposed to improve the classical NSGA-II. The results of employing the hybrid algorithm showed that the proposed algorithm not only improves the obtained solutions quality but also provides less CPU time for finding near-optimum solutions compared to classical NSGA-II. In addition, hybridization of the FA with NSGA-II may provide new insights on the application of the hybrid methods in the context of supply chain planning.

The analysis of numerical results provided important practical implications for both policy makers and mangers. For policy makers we showed flexibility in carbon emission could let firms to fulfill their needed cap with lower cost. In addition, while it is expected a tighter carbon cap reduce total carbon emission, one of the more significant findings to emerge from this study demonstrated that tighter carbon cap in JIT distribution can paradoxically led to end up with higher total carbon emission. For mangers, we showed that different carbon emission constraints could influence the average inventory holding and backlog level. It may help them to understand the encounter challenges (from investment

Table A1
Parameters of the instance.

Parameters	Total demand	Transportation cost	Backlog cost	Unitary carbon emission	Emax
Period 1	2A	1	1	1	A
Period 2	0	1	1	1	A

perspective) for distribution planning under carbon emission limitations.

Future works need to be done to establish integrated models in which production and operational decisions are also concurrently addressed. Another possible area of future research could be conducted to take the social and sustainable perspectives for further development of the proposed model. The following future directions can also be drawn from the present study: (i) Considering perishable products would be an interesting direction for further development of the proposed model since the products expiry dates influence products holding duration time in warehouse and order time. (ii) Considering the different transportation mode (e.g. air, rail or ship) with different carbon emission. (iii) Applying response surface methodology (RSM) to tune the parameters.

Appendix A.

Complexity analysis

In this section, we study the complexity of multi-echelon, multi- product and multi-period Distribution Network Problem with the Cumulative Carbon emission constraint (DNP-CC). For each period t, the average amount of carbon emission per product transported from the first period up to t should not exceed an impact limit $E^{\max}$.

Theorem 1. The DNP-CC is NP-Hard, even if only two echelons are considered and holding costs are null.

Proof. The reduction is done from the Partition problem. The partition problem is the task of deciding whether a given multiset S of positive integers can be partitioned into two subsets $S1$ and $S2$ such that the sum of the numbers in $S1$ equals the sum of the numbers in $S2$. In other words, given N integers such that $\sum_{i=1}^{N} a_i = 2A$, the decision problem consists in answering the question: Is there a set $S \subseteq \{1, \ldots, N\}$; such that $\sum_{i \in S} a_i = A$? The proof is based on the construction of an instance I of the DNP-CC problem considering a single distributor and multi-retailers (N retailers) in a distribution network with two periods. The demand of all retailers is expressed in the first period. Each retailer i has a demand a_i at the first period. The sum of the demands of the first period is equal to 2A while the sum of demands of the second period is 0. Holding costs are zero, while the other parameters are given in Table A1. □

We want to show that the partition problem is feasible if and only if there exists a feasible solution to instance I with a total cost at most $N + A$. If the instance of the partition problem has a feasible solution, then it exists S such that $\sum_{i \in S} a_i = A$. We can build a valid solution for instance I of the DNP-CC problem by shipping a maximum possible product quantity in the first period. In such a situation, the supplying cost is at least equal to N for transporting A products (since the cap is equal to A) plus the backlogging cost of A product to the second period. Consequently, the supplying cost is at least $N + A$. Suppose that we decide to satisfy the demands at the end of second period. In such situation, the optimal solution is to transporting an amount of 2A products to satisfy all demands. The supplying cost is equal to N which is divided between 2 periods. If we decide to split a demand between two periods, we need to supply this demand twice. In such a solution, we cannot split a demand otherwise the supplying cost is higher than N. Consequently, the demand of each retailer should be transported at once, then, we should have a partition, and if we have a partition, we should have A in delivered quantity in each period. We can conclude that a set S can be defined a valid partition for our instance.

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