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SUSTAINABLE MULTI-PRODUCTS DELIVERY ROUTING NETWORK DESIGN FOR TWO-ECHELON SUPPLIER SELECTION PROBLEM IN B2B E-COMMERCE PLATFORM

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Abstract. This paper examines the environmental impact produced by multi-vehicle transportation on a sustainable supply chain (SC) network. The relevance of green principles is gaining momentum day by day, which has forced the governments to introduce carbon emission schemes for the transportation associated with the firms. Various countries around the globe are introducing carbon-pricing schemes, in which a carbon tax is imposed based on the amount of anthropogenic emissions. A firm, which sets environmental standards for the emission associated with its operational activities, should design a transportation network based on the trade-off between its economic efficiency and the carbon emission. In this paper, the main focus is to design a sustainable supply chain network. A mixed-integer-non-linear-programming (MINLP) model is formulated to minimize the overall cost incurred in a multi-vehicle, multi-product sustainable transportation network. The meta-heuristic approach *i.e.*, Hybrid Chemical Reaction Optimization Algorithm with Tabu search (CRO-TS) and LINGO solver have been used to solve the proposed model. This analysis can guide the government to encourage the logistics service providers to capitalize on anthropogenic gas emission systems and simultaneously design the tax policy on carbon emission.

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1. Introduction

In the recent era, the e-commerce marketplace is booming in the business world, and especially the B2B e-commerce business has generated an extensive market opportunity to the logistics service provider and the online retailers. Though, facing the structural alterations in the B2B e-commerce logistics orders, the logistics operations without any transformation at the distribution centers the logistics service providers are experiencing

Keywords. Sustainable transportation network design, multi-vehicle transportation, carbon emission, chemical reaction optimization algorithm, tabu search, LINGO.

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serious challenges during orders handling in B2B e-commerce platform [45]. The relevance of green principles is gaining momentum day by day, which has forced the governments to introduce carbon emission schemes for the transportation associated with the firms. Various countries around the globe are introducing carbon-pricing schemes, in which a carbon tax is imposed based on the amount of anthropogenic emissions. A firm, which sets environmental standards for the emission associated with its operational activities, should design a transportation network based on the trade-off between its economic efficiency and the carbon emission. Logistics management plays a vital role in driving economic efficiency, which defines the existence of any firm or E-commerce platform. The network design is an essential element in decision making related to logistics management and it requires proper optimization of all the activities taking place in the e-commerce supply chain. Different aspects of the SC such as locations and number of facilities, types of facilities and their capacities, etc. are to be kept in mind while designing a network. A survey has been performed by Vidal and Goetschalckx [39], on different studies dealing with production distributions problems. Every firm aims to minimize the overall cost incurred through various activities. Hence, the proper optimization of every activity associated with the functioning of an SC network is essential to maximize the profit acquired.

Transportation is the most significant aspect of e-commerce supply chain management (SCM). A major portion of the logistics cost associated with a firm comes from the transportation in its SC. It imposes a large influence on the performance of logistics systems. According to Sreenivas [33], transportation contributes one-third of the total logistics cost of any manufacturing company. Transportation is necessary for different stages of the production process, from activities taking place in the manufacturing firm to the final delivery of orders to the customers. The proper coordination between different stages and processes is required to maximize the revenue produced by the company. The same product can be transported from one location to another by using different vehicles. Each vehicle incurs different costs for the same process. Similarly, the selection of the route for transportation of the product is also important as it forms an integral part of the transportation network. Another challenge that needs to be addressed is the air pollution produced in the operational phase, which causes a huge impact on greenhouse effects.

Transportation in SC networks is a major source of air pollution. The burning of fossil fuels to provide power to transport vehicles emits anthropogenic gas. *i.e.*, carbon dioxide (CO_2), which is one of the major causes of global warming. Pollution is known to produce health problems in humans and, also accounts for global warming. Global warming shows a rising trend every year (https://climate.nasa.gov/scientific-consensus/). Personal vehicles are one of the chief sources that contribute to global warming. Cars and trucks contribute about twenty percent to the total carbon emission in the US. According to Rao *et al.* [29], the transport sector accounts for 13% of the global greenhouse gas emission (GHG) and 23% of the energy comes from CO_2 emissions. Survey reveals that 75% of the emissions related to transportations are produced by road traffic. The global emissions from transportation are predicted to grow by 80% from 2007 to 2030 if proper measures are not taken to curb the emission. Global warming poses a threat to human health, endangers national security, and puts basic human needs on the line. The unusual and frequent occurrence of record global temperatures, the rise in sea level, and severe droughts and floods around different parts of the world can be characterized as the solutions to these emissions. The government of South Africa is trying to develop a sustainable network where "eco-friendly" vehicles are the preferred transportation option for a firm or a company [30]. This aids the government in successfully implementing Long Term Mitigation Scenarios (LTMS) that address climate changes issues and, policies associated with it. Roadways are the fastest-growing emitting sector and it brings with it the most complex challenges as it is associated with fuels, infrastructure, vehicle technology, and even behavioral changes. LTMS proposes a full-scale package design, addressing the wide range of interventions in this sector. A modal shift in the way freight movement takes place, and replacement of petrol and diesel with better alternatives acts as the mitigation wedges that need to be addressed. The spread and success of the mitigation will depend on the development and reliability of new sources of energy such as biofuel, electricity, or hydrogen.

Traditional models focus on optimizing costs involved in the SCM without considering the pollution factor. As the environmental aspects have become inevitable, the government has earmarked heavy prices for carbon emissions associated with each vehicle. The carbon tax will form an integral part of the overall cost of transportation if proper measures are not taken to keep them in check. Hence, the concept of green networks has been introduced in the roadways transportation network system. Usually, SCM deals with balancing the influence of time *versus* cost. This is visible in the transportation phase of SCM.

This paper addresses a problem related to greenhouse gas emission in roadways transportation network design related to delivery operations in B2B e-commerce platform. This study is performed to create a transportation model for a sustainable network design with multi-vehicle, multi-product aspects taken into consideration. The carbon emission taking place during the travel time of the vehicle is considered in this model. The travel velocity of each vehicle is defined by the lead-time provided by the demand zones, which further helps to determine the amount of emission based on the green velocity limits. To solve the mathematical model formulated, a hybrid of the Chemical Reaction Optimization (CRO) algorithm with a TS-based local search is suggested considering the faster convergence and higher solution produced by the algorithm. LINGO solver is used to validating the solutions obtained from the proposed meta-heuristic approach.

The rest of the paper is arranged as: Section 2, provides the details regarding existing literature concerning transportation problems. Section 3, provides a detailed description of the problem taken into consideration. Section 4, contains the model developed for the problem and the constraints associated with it. Solution and analysis of the model developed are given in Section 5. Section 6, provides the conclusion along with future work possibilities in this field.

2. Literature review

Most appropriate works in the sustainable network are about operational decisions, in general, taking a few aspects together. However, our proposed method has a dissimilar viewpoint and concentrates on one particular aspect of the green SC. Transportation network design forms an integral fragment of the efficient SC network. Hence, optimization of the transportation phase becomes very important. The literature review is divided into three sections: (1) B2B E-commerce businesses: provides the literature related to B2B E-commerce businesses. (2) Sustainable supply chain network: gives literature concerning studies related to supply chain network design problems. (3) Solution Approach: discussed different approaches followed to tackle these types of problems.

2.1. B2B e-commerce businesses

The leading industries are reshaping inter-organizational transactions processing, alliance, and trading into a competitive edge just because of the use of B2B e-commerce by Claycomb *et al.* [4]. Zhang *et al.* [43], proposed a collaborative transportation service trading problem related to B2B e-commerce logistics, in which they mainly focused on the collaborative problem of the less-than-truckload carriers with multiple logistics service providers. Xu *et al.* [41], proposed efficient intermodal transportation auctions related to the business-to-business e-commerce logistics concern. They have observed that the e-commerce platform plays the role of shipper in which the number of orders generated in between products buyers and sellers, and for the orders, fulfillment 3PLs can be used. The vehicle routing problem with the multiple depot's simultaneous pickups and delivery operations with time windows is considered for study related to e-commerce logistics system [45]. For the logistics service providers; to hold the marketplace of the distribution and logistics sector of the e-commerce with the help of improving the principal capability of an order handling in B2B e-commerce platform at their distribution depots [13]. They proposed a new approach to execute the B2B order pre-processing systematically for the logistics service providers so that the received orders at the B2B e-commerce platform are properly managed. Also, they have developed an intelligent B2B order handling system for effective and efficient management of frequently as well as discrete orders arrived at the B2B e-commerce platform.

2.2. Sustainable supply chain network

Transportation is the most important factor as far as the reliability of the SC is concerned. The Green SCM concept has been introduced to address the environmental issues that affect the traditional SCM. A detailed study on sustainable SC is performed by Srivastava [34]. Ramudhin *et al.* [28], proposed a most cost-effective SC network design, incorporating carbon offsets into cost and footprint calculations to optimize where carbon credits should be purchased and applied. The model is developed based on user-defined greenhouse gas reduction targets. A linear programming mathematical formulation is developed by Paksoy *et al.* [24], to evaluate the trade-off between functioning costs and environmental costs during the transportation for product recovery. Very few designs have attempted to optimize the product flow by focusing on the route design for the shipping network. Hence, vehicle routing models are producing an enormous impact on the design of an efficient transportation model. Elhedhli and Merrick [8], proposed a model considering CO_2 emission from vehicles along with the transportation phase for SC design. They suggested a model based on the relationship between vehicle weight and CO_2 emission. Transportation decisions produce a profound impact on the economic efficiency, along with the environmental performance of the SC [16]. A comparative study on the influence of environmental and cost factors on an SC is presented by Fahimnia *et al.* [9]. They stated that optimization of transportation and design of effective network systems are required to minimize the required resources, which assistances in the development of SC. Nouira *et al.* [23], proposed the design of a forward SC with carbon emission-sensitive demand taken into consideration. They assumed that; the demand is to be an endogenous variable dependant on carbon emission per unit. Nilsson [21], focused on how to elaborate the assumptions and perspectives embedded in the intricacy paradigm, which contribute to the research on logistics management to make it better aligned with genuine logistics. They observed that; it is essential just because of the difficulty increases in the supply chain due to the increasing demand for sustainable development. Noh and Kim [22], introduced one such contract between the multiple retailers and the single manufacture with limited resources for the variety of the products under the rules of greenhouse-gas emission. In that contract, the orders placed by each retailer for purchasing of products regularly within a warehouse capacity and limited budget, and manufacture produces products as per the requirement of the retailer and deliver them to the retailer warehouse after inspections. Tang *et al.* [37], proposed a hierarchal Bayesian network model used for quantitative evaluation of the resilience of the urban transportation systems. Stefaniec *et al.* [35], suggested the triple bottom line-based systematic approach to evaluate road transport with considering the economic, environmental, and social factors of sustainability, which helps decision-makers for better assessment of the performance of the transport sustainability. The logistics operations are in main transportation, giving a structure for the delivery of the product on an international scale [31]. Two-echelon location routing problem along with time constraints and transportation resource sharing is considered for study [40, 42]. Anderluh *et al.* [2], focused on two-echelon multi-objective VRP with grey zone customers arising and vehicle synchronization of freight deliveries in an urban context.

2.3. Solution approach

The application of Evolutionary Algorithms (EAs) to solve various network design and transportation-related problems are showing a rising trend nowadays due to their high flexibility and scalability, their capability to solve global optimization problems and optimize various criteria for feature selection at the same time, for instance, selection, and other data lessening issues. It is used to solve Non-deterministic Polynomial-time (NP) hard category problems as it can give near-optimal solutions. Obtaining exact solutions to these problems is very challenging. So EAs are employed to obtain the best possible solution. Shaw *et al.* [32], used Bender's decomposition algorithm to develop a minimum carbon chance-constrained SC network. Taylor *et al.* [38], introduced a method based on ACO to solve a resource-allocation problem that considers single period, single product, and the infinite capacity of the DCs. They displayed the better performance quality of the ACO-based heuristic over the basic GA through statistical analysis. Similarly, different algorithms and approaches are developed for solving problems related to different aspects of the SC. Chemical Reaction Optimization (CRO) is a meta-heuristic proposed by Lam and Li [11]. It is inspired by molecular chemical reactions. They have proved CRO to be most effective in answering a variety of optimization problems. An efficient evolutionary algorithm which is a hybrid of CRO and Particle Swarm Optimization was developed by Nguyen *et al.* [20]. The computational solutions showed significant deviate and improvement over basic CRO. A hybrid of CRO was introduced by Li and Pan [14], by combining CRO with Tabu Search (TS) based operator. This algorithm displayed improved solution quality and was used to solve a quadratic model developed to maximize the profit generated in a monopolist firm that served an environmentally sensitive market. Abyazi-Sani and Ghanbari [1], improved the computation time of TS-based local search by introducing a few new rules into the TS. This was successfully implemented to solve the un-capacitated facility location problem for a single allocation hub. The Tabu Search heuristic has also been used by Cordeau *et al.* [5], to solve periodic and multi-depot vehicle routing problems. Three famous routing problems; the periodic traveling salesman problem, the periodic VRP, and the multi-depot VRP, were taken into account. Computational analyses carried out in instances indicated that the proposed algorithm outperformed heuristics such as GA for all three problems. However, very few studies have used TS heuristics embedded into CRO to answer the problems related to transportation in a green SC. Zhang *et al.* [45], used the simple genetic algorithm (GA), block-based GA, and parallel differential evolutionary algorithm to solve the optimization model related to the minimization of the total transportation cost with penalty due to delay by the LSPs. Dwivedi *et al.* [7], introduced an MINLP model which helps to minimize the total shipping and carbon emission taxations costs during the collection of food grains from different former locations and used LINGO solver and meta-heuristics (GA and quantum-based GA) for the solution purpose of the model. There are many research articles published that used the LINGO optimization tool for the solution of the optimization models based on the logistics and SC network design [3, 15, 18].

3. Problem description

In this problem, a multi-product single-period supply chain in an e-commerce platform is being considered. The network consists of factories, distribution centers (DCs), and demand points. We have considered distribution centers as a whole seller like IndiaMart, Alibaba, etc. who manage their inventory levels and sell to the retailers (customers) like Walmart, Big-Bazar, V-Mart, etc using B2B e-commerce business model. The manufacturer sends their manufactured products to the distribution centers furthermore, the distribution center sells products to the customers. Depending upon the requirement at a particular point of time, the demand point places the order for the type of products required. They also provide a lead-time for receiving the product. Goods will be carried out from the factory to the DC using different vehicles available at each factory. DC uses different types of vehicles for transportation of the products received from the factories. The goods are then transported to the respective demand points based on the order. In this model, only the transportation aspect of the SC is taken into consideration. The factories and DCs in this SC are not associated with any capacity constraints.

Vehicles with different capacities are available at each location and there is no restriction placed on several vehicles available at each location. During the transportation phase, carbon dioxide emission takes place due to the consumption of fuel. Speed within a particular range is observed to emit the least amount of carbon. Even during idle time, the vehicle consumes fuel and hence more carbon emissions take place. The products have to reach the demand points within the prescribed lead-time and the vehicle has to keep its speed within a particular range to minimize the emission involved in transportation. The overall cost incurred will increase with an increase in carbon emission. Depending upon the carbon emission of the vehicle, a carbon tax is levied. The greenness of the SC is taken into consideration, accompanied by minimization of the cost along with the SC. In the present scenario, owing to the increased traffic and the short lead times provided by the demand points it becomes mandatory to select an optimized route for transportation. Hence, a trade-off between the route selected and the speed of travel is important to decrease the overall cost. The concept of greenness is embedded in this model concerning the transportation phase, which forms the operational part of the SC. This model aims to reduce the overall cost involved in the shipping of goods, which includes the vehicular cost for covering the distance and the carbon tax levied on each vehicle based on the constraints that will be defined later in the mathematical model. Figure 1 gives a schematic representation of the flow of material taking place in an SC.

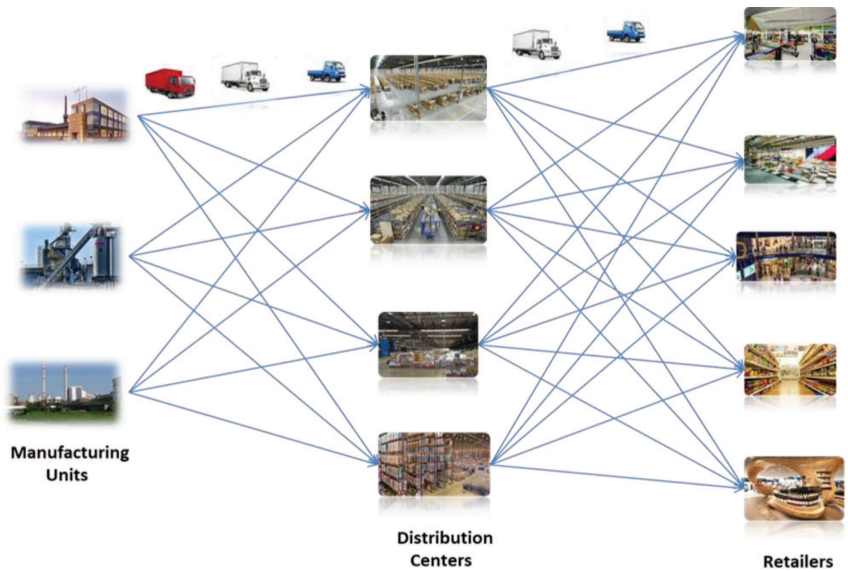

FIGURE 1. Schematic diagram of material flow in a supply chain network.

Mathematical model

Sets

FT	Set of factories
DTC	Set of distribution centers (DCs)
CL	Set of customer locations or demand points
VH	Number of vehicles available at each factory
VH′	Number of vehicles available at each DC
P	Set of products

Indices

f	Indexing for factories $\{f = 1, 2, \ldots, F\}$
d	Indexing for distribution centers (DCs) $\{d = 1, 2, \ldots, D\}$
c	Indexing for customer locations or demand points $\{c = 1, 2, \ldots, C\}$
v	Number of vehicles available at factories and DCs $\{v = 1, 2, \ldots, v' \ldots, V\}$
i	Indexing for a set of products $\{i = 1, 2, \ldots, I\}$

Parameters

o_v	The capacity of vehicle v available at factory
$t_{v'}$	The capacity of vehicle v' available at the DC
j_{ci}	Demand for the product i at demand point c
S_v	The average speed of a vehicle v, $v \in V$
$S_{v'}$	The average speed of a vehicle v', $v' \in V$
m_v	Minimum speed allowed for a vehicle v, $v \in V$, $v' \in V$
M_v	The maximum speed allowed for a vehicle v, $v \in V$, $v' \in V$
U_v	Range of speed (m_v, M_v) for a vehicle v to exhibit minimal carbon emission
X_{fd}	Distance between factory f and DC d
Y_{dc}	Distance between DC d and demand point c

π Shipping cost imposed in between factory to DC (in \$/Km/vehicle)
π' Shipping cost imposed in between DC to demand points (in \$/Km/vehicle)
LT_i Lead time for delivery of product i
K_d Storage capacity of DC d
W_f Production capacity of factory f
€ Carbon tax imposed when a vehicle traveling within speed range U_v
Ψ Carbon tax imposed when a vehicle traveling beyond speed range U_v

Variables

H_{fdvi} Quantity of product i shipped from factory f to DC d using vehicle $v, v \in V$
$B_{dcv'i}$ Quantity of product i shipped from DC d to demand point c using vehicle $v', v' \in V$
N_1 Number of vehicles of type v traveling from factory f to DC d with the product i
N_1' Number of vehicles of type v' traveling from DC d to demand point c with the product i
N_2 Number of vehicles traveling between factory f and DC d with speed beyond the optimal range
N_2' Number of vehicles traveling between DC d and demand point c with speed beyond the optimal range
N_3 Number of vehicles traveling between factory f and DC d with speed within the optimal speed range
N_3' Number of vehicles traveling between DC d and demand point c with speed within the optimal speed range
g_{fdvi} If vehicle v moves from factory f to DC d with product i, then 1, otherwise 0
$g'_{dcv'i}$ If vehicle v' moves from DC d to demand point c with product i, then 1, otherwise 0
h^1_{fdv} If vehicle v moves between factory f and DC d at beyond the speed range U_v, then 1, otherwise 0
$h^{1'}_{dcv'}$ If vehicle v' moves between DC d and demand point c at beyond the speed range U_v, then 1, otherwise 0
h^2_{fdv} If vehicle v moves between factory f and DC d at within the speed range U_v, then 1, otherwise 0
$h^{2'}_{dcv'}$ If vehicle v' moves between DC d and demand point c at within the speed range U_v, then 1, otherwise 0

Objective function

$$\begin{aligned}
Z_{\min} = {} & \sum_{f\in F}\sum_{d\in D}\sum_{v\in V}\sum_{i\in I}\pi X_{fd}N_1 g_{fdvi} + \sum_{d\in D}\sum_{c\in C}\sum_{v'\in V}\sum_{i\in I}\pi' Y_{dc}N_1' g'_{fdv'i} \\
& + \Psi\left\{\sum_{f\in F}\sum_{d\in D}\sum_{v\in V}\sum_{i\in I} X_{fd}N_2 h^1_{fdv} g_{fdvi} + \sum_{d\in D}\sum_{c\in C}\sum_{v'\in V}\sum_{i\in I} Y_{dc}N_2' h^{1'}_{dcv'} g'_{fdv'i}\right\} \\
& + \text{€}\left\{\sum_{f\in F}\sum_{d\in D}\sum_{v\in V}\sum_{i\in I} X_{fd}N_3 h^2_{fdv} g_{fdvi} + \sum_{d\in D}\sum_{c\in C}\sum_{v'\in V}\sum_{i\in I} Y_{dc}N_3' h^{2'}_{dcv'} g'_{fdv'i}\right\}.
\end{aligned} \tag{3.1}$$

Subjected to constraints

$$\sum_{f\in F}\sum_{d\in D}\sum_{v\in V}\sum_{i\in I} H_{fdvi} g_{fdvi} \le K_d \tag{3.2}$$

$$\sum_{d\in D}\sum_{c\in C}\sum_{v'\in V}\sum_{i\in I} B_{dcv'i} g_{dcv'i} \le W_f \tag{3.3}$$

$$\sum_{f\in F}\sum_{d\in D}\sum_{v\in V}\sum_{i\in I} H_{fdvi} g_{fdvi} = \sum_{d\in D}\sum_{c\in C}\sum_{v'\in V}\sum_{i\in I} B_{dcv'i} g'_{dcv'i} \tag{3.4}$$

$$\sum_{f\in F}\sum_{d\in D}\sum_{v\in V}\sum_{i\in I} H_{fdvi}g_{fdvi} = \sum_{c\in C}\sum_{i\in I} J_{ci} \tag{3.5}$$

$$\sum_{d\in D}\sum_{c\in C}\sum_{v'\in V}\sum_{i\in I} B_{dcv'i}g'_{fdvi} = \sum_{c\in C}\sum_{i\in I} J_{ci} \tag{3.6}$$

$$\frac{X_{fd}}{S_v}\left(h^1_{fdv}+h^2_{fdv}\right)+\frac{Y_{dc}}{S_{v'}}\left(h^{1'}_{dcv'}+h^{2'}_{dcv'}\right)\le \mathrm{LT}_c, \qquad \forall f\in F, d\in D, c\in C, v\in V, v'\in V \tag{3.7}$$

$$S_v \in U_v, \qquad \forall v\in V \tag{3.8}$$

$$S_{v'} \in U_v, \qquad \forall v\in V, v'\in V \tag{3.9}$$

$$N_1 = \frac{\sum_{f\in F}\sum_{d\in D}\sum_{i\in I} H_{fdvi}g_{fdvi}}{o_v}, \qquad \forall v\in V \tag{3.10}$$

$$N'_1 = \frac{\sum_{d\in D}\sum_{c\in C}\sum_{i\in I} B_{dcv'i}g'_{dcv'i}}{t_{v'}}, \qquad \forall v'\in V \tag{3.11}$$

$$H_{fdvi}, B_{dcv'i} \ge 0, \qquad \forall f\in F, d\in D, c\in C, v\in V, i\in I \tag{3.12}$$

$$n_{fdvi}, N_{dcv'i}, L_{fd}, L'_{dc}, A_{fd}, A'_{dc} \in z^+ \tag{3.13}$$

$$g_{fdvi}, g'_{dcv'i} = \{0,1\}, \qquad \forall f\in F, d\in D, c\in C, v\in V, i\in I \tag{3.14}$$

$$h^1_{fd}, h^{1'}_{dc} = \{0,1\}, \qquad \forall f\in F, d\in D, c\in C \tag{3.15}$$

$$h^2_{fd}, h^{2'}_{dc} = \{0,1\}, \qquad \forall f\in F, d\in D, c\in C. \tag{3.16}$$

In objective function (3.1), terms 1 and 2 represent the cost of shipping products from factory to distribution center and distribution center to demand points respectively, terms 3–6, together gives the total carbon tax payable for speeds attained during the whole transportation. Terms 3 and 4, compute the carbon tax when the vehicle moves beyond the speed range in between factory to DC and DC to demand points, respectively. Terms 5 and 6, compute the carbon tax when the vehicle moves within the speed range in between factory to DC and DC to demand points, respectively. Constraints (3.2), and (3.3) are the capacity constraints. Constraint (3.2), makes sure that the DC has enough space to receive the products coming from factories. Constraint (3.3), shows that the factory should have enough capacity to satisfy the quantity moving from DC to fulfill the order received from demand points. Constraint (3.4), ensures the balance between products delivered at the DC and departed from DC to the demand points. Constraints (3.5), and (3.6), are the demand constraints. Constraint (3.5), checks the equality between the order given from demand points and the quantity of products pickup from the factories. Constraint (3.6), checks the equality between the order given from demand points and the quantity of products pickup from the DCs. Constraint (3.7), Constraints (3.8), and (3.9) are the constraints related to defining the limit of the speed reached by a vehicle during transportation to minimize carbon emissions. Constraints (3.10), and (3.11), give information about the minimum number of vehicles that should run from factories and DCs to satisfy the demand for an item. Constraint (3.12), is a structural constraint related to variables' non-negativity and integrity. The integer variables are represented by Constraint (3.13). Constraint (3.14), represents the binary decision variables related to the vehicle v moving from the factory to DCs with product i, and the vehicle moves from DCs to demand point c with product i, respectively. Constraint (3.15), represents the binary decision variables related to the vehicle moves between factory and DCs beyond the speed range U_v, and the vehicle moves between DCs and demand point beyond the speed range U_v, respectively. Constraint (3.16), represents the binary decision variables related to the vehicle v moves between factory and DCs within the speed range U_v, and the vehicle v' moves between DCs and demand point within the speed range U_v, respectively.

4. Solution methodology

The capacitated VRP is solved by using the CRO with unified tabu search heuristic and the CRO approach has proved for the solution purpose of NP-hard problems as the traveling salesman problem, neural networking training, and quadratic assignment problem in an effective manner [6]. The multi-model multi-period bulk wheat storage and transportation problem in an SC network are formulated by the MINLP approach and solved by the CRO algorithm with tabu search [17]. Hybrid CRO performs better than the other metaheuristics methods such as particle swarm optimization (PSO), genetic algorithm (GA), ant colony algorithm (ACA), bee colony algorithm (BCA) [6, 19, 36, 44]. Hence, we have used the hybrid CRO with TS to solve our proposed MINLP model.

4.1. Hybrid chemical reaction optimization with tabu search (CROTS)

The CRO is an optimization technique, which performs its operations based on basic principles of a chemical reaction. It does not require every aspect of chemical reactions for performing the optimization. The first law of thermodynamics (or the law of conservation of energy), and the second law of thermodynamics (Entropy of a system always tends to increase) together form the governing principles of a chemical reaction. A system subjected to a reaction consists of a substance and its surrounding. Any Substance would always have some amount of potential energy or kinetic energy associated with it. The CRO consists of a central energy buffer, which means energies of the surroundings. The energy possessed by the molecule by virtue of its configuration is called Potential energy, which creates disorder in the system when converted to other forms. Every system tries to associate itself with the least potential energy (stability), which is achieved by reaching the state of equilibrium. A chemical reaction always tries to produce stable products *i.e.*, with the least potential energy. In CRO, some of the potential energy is converted into kinetic energy, and the remaining is gradually transferred to the surroundings to produce a stable product. This is a stepwise process, which helps to search for the optimal point. The molecules, when inside the container, undergo collisions. The collisions indicate molecular interactions. The collisions might be with the container walls or other molecules. This triggers a structural change in the molecules. The collisions trigger elementary reactions and the energy associated with each molecule that has undergone the collision is evaluated. Four different elementary reactions are generally performed by a CRO. Two of the reactions are intermolecular reactions and the other two are uni-molecular in nature. Decomposition and On-wall ineffective collision (OIC) comes under uni-molecular reactions. Synthesis and Intermolecular collision belong to the category of intermolecular collisions. Two of the collision reactions-Intermolecular and wall collision-are convergent in nature. They introduce the intensification or local search. Synthesis and decomposition are divergent in nature. They introduce diversification into the search process. The intensification and diversification in the right proportion lead to the global optima.

The basic building block of CRO is a molecule. Each molecule is associated with definite attributes such as kinetic energy (KE), potential energy (PE), molecular structure (ω). In this problem, ω is a structure, which consists of integer and continuous decision variables. It gives the solution to the problem. PE gives the value of the objective function produced for a particular molecule. The tolerance for the worst solution and the ability to escape from the local minimum is represented by KE. There are a few other attributes that characterize the molecule when it goes through a collision. *NumHit* represents the number of collisions undergone by the molecule. *Minstruct* represents the configuration of least potential energy attained in the population by a molecule. The objective function value or the PE corresponding to *Minstruct* is represented by *MinPE*. The number of collisions undergone by a molecule, before it achieves configuration is given by *MinHit*.

CRO operates through three stages-Initialization, Iteration, and Termination. The algorithm is initialized with the below-mentioned parameters in the initialization phase. The pseudo-code for the initialization phase is known in Figure 2, α and β are used to regulate the degree of intensification and diversification involved in the search process. The population size of the problem is given by *PopSize*. *KELossRate* gives the rate of loss of kinetic energy taking place during an elementary reaction. *MolColl* is used to decide between uni-molecular and multimolecular reactions.

The four elementary reactions are:

(1) On-wall ineffective collision (OIC): here, it is seen that the molecule strike against the walls of the container and gets the rebound. A small change in potential energy is observed as the solution of a change in molecular

Algorithm 1 "Molecule Initialization"

```
class Molecule
        Attributes of molecule:
          Assign values of ω, KE, PE, MinStruct, MinPE, MinHit, NumHit
        Method:
          Molecule () \\constructor
          {
                Create ω in solution space randomly
                Calculate PE = f (ω)
                Set KE = InitialKE
                Set NumHit = 0
                Set MinStruct = ω
                Set MinPE = PE
                Set MinHit = 0
          }
          On wall Ineffective Collision ()
          Decomposition ()
          Intermolecular Ineffective Collision ()
          Synthesis ()
      end class
```

FIGURE 2. Pseudocode for molecule initialization.

structure. The new molecule is obtained by using a neighborhood operator. The change occurs only if:

$$\mathrm{KE}_{\omega} + \mathrm{PE}_{\omega} \geq \mathrm{PE}_{\omega'}. \tag{4.1}$$

We get,

$$\mathrm{KE}_{\omega'} = (\mathrm{KE}_{\omega} + \mathrm{PE}_{\omega} - \mathrm{PE}_{\omega'}) \times a. \tag{4.2}$$

If the condition is not satisfied, the collision of the molecule is not allowed and the molecule will remain as part of the population without any change in its configuration. The value of a is set by randomly selecting a number from the interval $[KELossRate, 1]$. $(1-a)$ denotes the portion of the kinetic energy that is lost to the surroundings and the remaining goes to the central buffer which can be later used by operators that require the intake of energy. Figure 3 gives the pseudo-code for the OIC.

(2) Decomposition: it takes place whenever a molecule hits with a wall and it separates into two or more molecules. Energy will be required for the formation of these molecules. The central energy buffer provides the required energy. The characteristics of the new molecule will be entirely different from the original molecular structure. Two randomly generated numbers δ_1 and δ_2 determine the energy amount introverted from the central buffer by each molecule. Here, δ_1, δ_2 are two numbers taken from the range $[0, 1]$.
The energy conservation for decomposition is given by:

$$\mathrm{PE}_{\omega} + \mathrm{KE}_{\omega} + \delta_1 \times \delta_2 \times \mathit{buffer} \geq \mathrm{PE}_{\omega 1'} + \mathrm{PE}_{\omega 2'}. \tag{4.3}$$

If the condition is satisfied, the molecule undergoes decomposition and two new molecules will be produced. The energy involved in the process is given by:

$$E_{\mathrm{dec}} = \mathrm{PE}_{\omega} + \mathrm{KE}_{\omega} + \delta_1 \times \delta_2 \times \mathit{buffer} - (\mathrm{PE}_{\omega 1'} + \mathrm{PE}_{\omega 2'}). \tag{4.4}$$

Algorithm 2 On wall Ineffective Collision (M, $buffer$)

Input: a molecule M with molecular structure ω i.e. M_ω and central energy buffer
Obtain the new molecule from neighboring approach, i.e. $\omega' = N(\omega)$
Calculate the $PE_{\omega'}$ by using $f(\omega')$ i.e. $PE_{\omega'} = f(\omega')$
if $KE_\omega + PE_\omega \geq PE_{\omega'}$ **then**
  Get a randomly in the interval $[KELossRate, 1]$
  Set $KE_{\omega'} = (KE_\omega + PE_\omega - PE_{\omega'}) \times a$
  Update $buffer = buffer + (KE_\omega + PE_\omega - PE_{\omega'}) \times (1\text{-}a)$
  Update the profile of M by $\omega = \omega'$, $PE_\omega = PE_{\omega'}$, $KE_\omega = KE_{\omega'}$
  if $PE_\omega < MinPE_\omega$ **then**
    Update the $MinStruct_\omega = \omega$, $MinPE_\omega = PE_\omega$, $MinHit_\omega = NumHit_\omega$
  end if
end if
Output: M and $buffer$

FIGURE 3. Algorithm: On wall ineffective collision.

The energy transfer to newly generated molecules is given by:

$$\mathrm{KE}_{\omega 1'} = \delta_3 \times E_{\mathrm{dec}} \tag{4.5}$$
$$\mathrm{KE}_{\omega 2'} = (1 - \delta_3) \times E_{\mathrm{dec}}. \tag{4.6}$$

δ_3 is a number randomly created from the range $(0, 1)$. Hence the energy in the central buffer becomes:

$$buffer' = (1 - \delta_1 \delta_2) \times buffer. \tag{4.7}$$

(3) Inter-molecular Ineffective collision: here, the multiple randomly selected molecules strike against each other and rebound. No new molecules are created, but the molecular arrangement of the colliding molecules will be compromised. The new molecular arrangement is obtained using a neighborhood search operator. Unlike OIC, KE is not haggard to the central buffer. The condition for this collision to take place is given by:

$$\mathrm{PE}_{\omega 1} + \mathrm{PE}_{\omega 2} + \mathrm{KE}_{\omega 1} + \mathrm{KE}_{\omega 2} \geq \mathrm{PE}_{\omega 1'} + \mathrm{PE}_{\omega 2'}. \tag{4.8}$$

Here energy is released and the energy released is given by:

$$E_{\mathrm{inter}} = \mathrm{PE}_{\omega 1} + \mathrm{PE}_{\omega 2} + \mathrm{KE}_{\omega 1} + \mathrm{KE}_{\omega 2} - (\mathrm{PE}_{\omega 1'} + \mathrm{PE}_{\omega 2'}). \tag{4.9}$$

δ_4 is a random number that helps to distribute the remaining energy in between the molecules.

$$\mathrm{KE}_{\omega 1'} = \delta_4 \times E_{\mathrm{inter}}; \quad \mathrm{KE}_{\omega 2'} = (1\delta_4) \times E_{\mathrm{inter}}. \tag{4.10}$$

(4) Synthesis: In this operator, the formation of a new molecule takes place as a solution to a collision between multiple molecules. It is the reverse decomposition reaction considering the series of events that take place. It occurs only if:

$$\mathrm{PE}_{\omega 1} + \mathrm{PE}_{\omega 2} + \mathrm{KE}_{\omega 1} + \mathrm{KE}_{\omega 2} \geq \mathrm{PE}_{\omega 1'}. \tag{4.11}$$

The newly generated molecule exhibits a much better exploration of solution space due to larger kinetic energy. This helps to induce diversification into the search.

In all the iterations, the global best solution is compared with the best solution obtained. If the solution produced in the current iteration is better than the global best, it will be stored in the memory. The iterations take place until it meets the stopping criterion and then the algorithm is terminated.

The decomposition and synthesis reactions produce significant changes in the molecule and solution in an entirely new molecular structure [14]. The remaining two elementary reactions produce very small changes in the molecular structure. Hence, it becomes clear that divergence required in the search is well implemented by basic CRO, but intensification requires improvement. Hence, Tabu Search (TS) is combined with basic CRO. This enhances the convergence ability and solutions in improved solution quality of the search operation. TS explores the solution space by performing the neighborhood search. This process brings more intensification into the search process. TS produces simple modifications to the solution. By using the solution (S_c) obtained from basic CRO, exploration of the solution space around the current solution is performed iteratively. A Tabu list is maintained to store recently generated solutions (S_n). The next best solution ($S_{c'}$) is selected from the Tabu List based on the aspiration criterion. Here, S_c represents the solution obtained from operations performed in basic CRO. S_n represents the solutions at present in the neighborhood of the recent solution. $S_{c'}$ represents the next best solution.

TS-based local search

Tabu Search operation:

(1) Calculate the recent (local) optimal solution using four basic elementary reactions.
(2) Let $g = 0$.
(3) The neighboring solution space of the current solution is explored to construct the neighbor set.
(4) Calculate the fitness values based on the solutions developed.
(5) Set the neighboring solutions based on their fitness values (in non-decreasing order).
(6) The next best solution is selected based on (a) Select a solution, which is not present in the Tabu list. If more than one solution occurs, select the solution that appears first. (b) If all the solutions are present in the Tabu list, then select the first solution, which has its objective function value greater than the recent optimal solution. Update the Tabu list and the global optima whenever a better solution is met from the neighbor search.
(7) Repeat steps 2–6 until the stopping criterion is fulfilled.

CROTS algorithm framework

Step I. Assign values to the parameters.
Step II. Initialization.
  Step (A). Set the values of all the control parameters: *MolColl*, *buffer*, α and *numNeighbour*.
  Step (B). Randomly creates *PopSize*, a number of molecules to develop a solution space.
Step III. Calculate the potential energy values of each member of the population.
Step IV. If the terminating condition (stopping criterion) is satisfied, the best solution is given as the output; otherwise perform steps (C) to (E).
  Step (C). Random selection of b from the range $[0, 1]$; If $b > MolColl$, perform the step (D), otherwise, perform the step (E).
  Step (D). Randomly selects any molecule from the population and perform decomposition or OIC, based on the decomposition criterion.
  Figure 4 depicts the two uni-molecular collisions.
  Step (E). Randomly pick any of the two molecules from the population, and perform Synthesis operation or Intermolecular Ineffective collision.
  Figure 5 illustrates the two intermolecular collisions.
Step V. Determine the optimal solution for the given population and perform the Tabu search operation.

A descriptive flowchart representing all the operations performed in the CROTS function is represented in Figure 6.

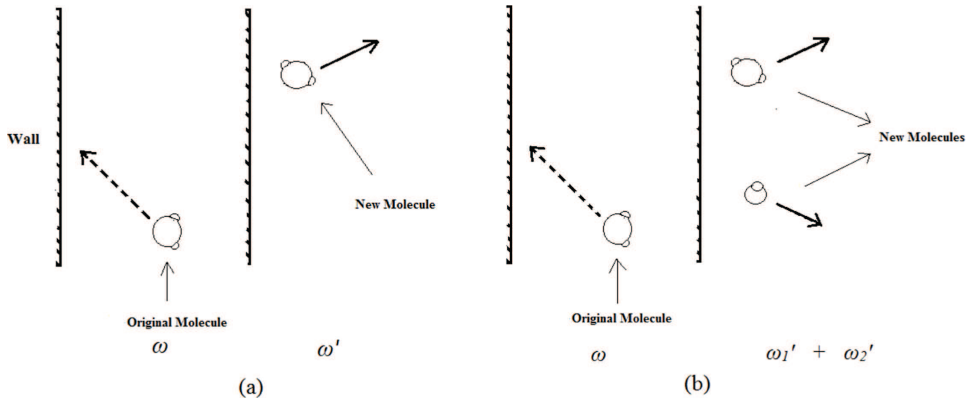

FIGURE 4. Single-molecule: (a) On wall Ineffective collision. (b) Decomposition.

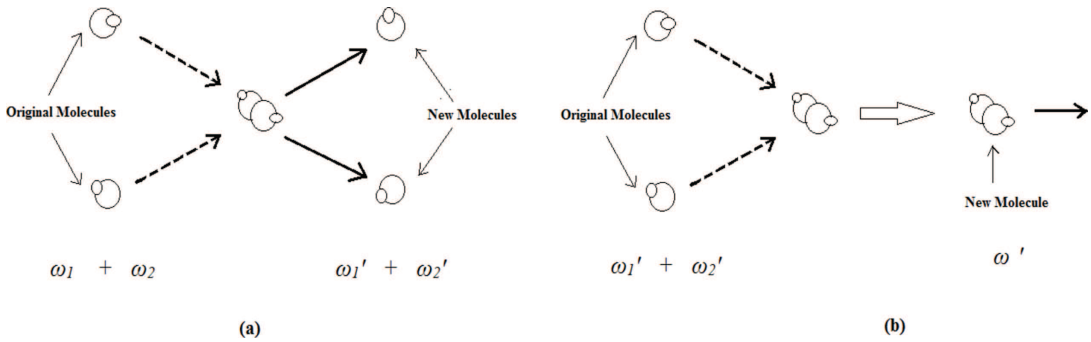

FIGURE 5. Multi-molecule: (a) Intermolecular Ineffective collision. (b) Synthesis.

4.2. LINGO solver

Lingo is a simple optimization tool, which developed for building and solving optimization problems efficiently and easily. This tool has the capability to solve all types of programming such as linear and nonlinear programming, integer and mixed-integer programming, quadratic programming, etc. The solution obtained from this is globally optimal because LINGO automatically selects the solution approaches such as branch-and-bound algorithm, branch-and-price algorithm, etc. to solve the optimization problem. Branch-and-Bound (B-and-B) and Branch-and-Price algorithms are the solutions approach generally applied to solve integer programming problems and can be used for the solution of several different varieties of optimization problems. The B-and-B approach works on the principle that the set of feasible solutions can be subdivided into the different smaller subsets of solutions and then these can be evaluated analytically until the best is obtained (Taylor B). The developed mathematical model for the two-stage supply chain with allocation-distribution is solved by using the LINGO optimization tool [10], the last-mile distribution problem related to fresh foods delivery [26], the minimization of time windows [25], and integrated supplier selection transportation and vehicle routing problems [27] in e-commerce platform which are formulated by using MINLP approach and solved by using the LINGO optimization tool.

In this paper, we used LINGO 18 on a computer with the Windows 10 environment, 8 GB RAM, and Intel Core i5, 2.9 GHz processor, to solve and get the global optimum solution of the problem. The main aim to choose this tool is to validate the solutions obtained from the heuristic techniques.

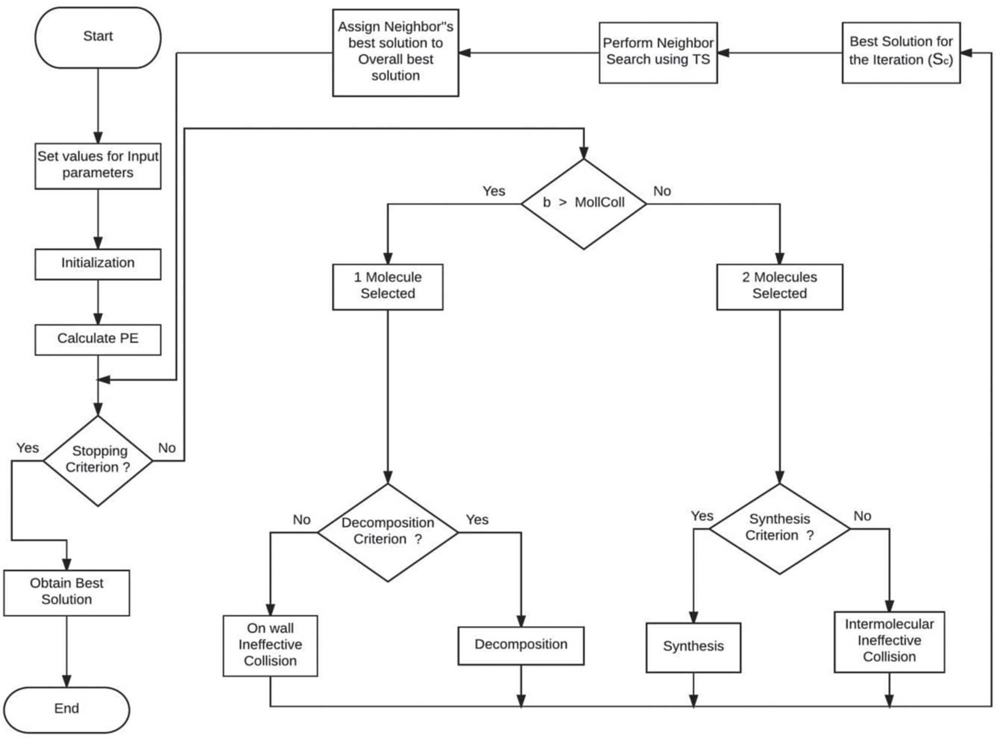

FIGURE 6. Flow Diagram representing different stages in CROTS.

5. Results and discussion

The e-commerce SC under consideration consists of a set of factories, DCs, and demand points. Each demand point might order different quantisties of each product. According to the order, each product will be manufactured in a factory, selected randomly. Each factory is provided with a variety of vehicles using which the manufactured products are taken to one of the DCs. The DC allocates the product to respective demand points based on the order received. The DC is also provided with different types of vehicles for delivering the products to the respective demand zones. While transporting the product, care is taken to ensure that the products are reaching the destination points within the lead times provided by the demand points. The factories and the DCs are set up in such a way that the whole demand for a particular product never exceeds their capacities. The objective is to reduce the overall cost involved in the transportation phase. Since this paper is interested in developing a sustainable transportation network, the emission has to be taken into account. In the model developed, a carbon tax is imposed based on the distance and speed of travel, and also the idle time. All these factors combine with the overall cost of the transportation network.

The proposed model focuses on minimizing the overall cost associated with the transportation phase for the delivery operation of B2B e-commerce orders. The solution methodology tries to give the most optimal solution possible for the problem addressed here in this paper. Here the model is solved using two algorithms-CRO and CROTS. Both the algorithms have been coded into a personal computer for solving the proposed model. The code was made in MATLAB R2014a on a personal computer with Windows 10 environment, 8 GB RAM, and Intel Core i5, 2.9 GHz processor. The values assigned to different parameters are illustrated in this section. The same problem is solved for a different number of nodes. Three cases are considered, each with a different number

TABLE 1. Parameters of CRO and CROTS.

Parameters	CRO	CROTS
PopSize	300	300
KELossRate	0.2	0.2
initialKE	40.36×10^6	40.36×10^6
MolColl	0.3	0.3
Alpha	3	3
Beta	40.34×10^6	40.34×10^6
Tabu length	–	10

TABLE 2. Parameters.

Parameter	Value
m_v	35
M_v	50
P	100
ν	10
Ψ	100

of factories, DCs, and demand points. Types of vehicles available at each factory, vehicles available at the DC, and products being manufactured also differ for all the cases considered in this paper.

The parameters associated with the meta-heuristics require proper tuning because it mostly affects the quality of the obtained solution from the algorithm [17]. The values of these parameters may change from problem to problem. The best solution is obtained when proper tuning is imposed on these parameters [11]. According to Lam *et al.* [12], for the tuning of parameters of metaheuristics, there is no type of theoretical guidelines are available. The adjustments of the parameters depend on the researcher's preferences and experience [17]. In this paper, we have considered a realistic scenario of an Indian e-commerce platform but due to the company policy, the simulated data sets for all the case scenarios have been validated and determined the best possible solutions. The code was executed for different runs with different runs and the parameter values associated with the least average overall cost have been selected. The parameters and their values that remain the same for all the test cases are shown in Tables 1 and 2. Table 1 gives the values of the parameters associated with the meta-heuristics-CRO and CROTS- used in this paper taken from [17] and Table 2 gives data related to some of the parameters in the mathematical model developed. Based on the solutions obtained from each test case, the performance of CRO and CROTS is evaluated. For each case, the algorithm is executed for 10 runs and corresponding solutions are obtained for CRO and CROTS.

Case 1 (3–3–4–2–2–3). In this case, the transportation network is considered to have 3 factories, 3 types of vehicles traveling from the factories, 4 DCs, 2 types of vehicles traveling from the DCs, 2 demand points, and 3 types of products are considered of being manufactured in each factory.

Table 3 gives the distance between each factory and DC in the network. The distance between each DC and the demand point is represented by Table 4. Table 5 shows the lead time provided by each demand point for the supply of the product. The storage capacity of each type of vehicle running in the SC and the capacities of each factory and DC are given in Tables 6–8, are represent the cost of transporting a product using a particular vehicle in each route in the given transportation network.

Similarly, Case 2 (5–4–6–3–3–4), Case 3 (8–5–9–4–5–5), Case 4 (3–6–4–5–10–7), Case 5 (5–8–6–7–15–12), (8–12–9–10–20–18), (3–18–4–16–30–25), (5–25–6–24–40–32) and (8–32–9–30–50–40) are solved using their corresponding input data, and the proposed algorithms. The solutions obtained are represented in Table 9.

TABLE 3. Values of X_{fd}.

	d_1	d_2	d_3	d_4
f_1	80	120	160	200
f_2	155	115	90	140
f_3	220	150	110	70

TABLE 4. Values of Y_{dc}.

	$c1$	$c2$
d_1	40	50
d_2	60	30
d_3	105	75
d_4	135	110

TABLE 5. Lead time provided for the supply of the product.

Demand points	c_1	c_2
Lead Time (LT_c)	5	6

TABLE 6. Storage capacity of each type of vehicle, the capacities of each factory and distribution center.

Parameters	o_1, o_2, o_3	t_1, t_2	W_1, W_2, W_3	K_1, K_2, K_3, K_4
Values	2000, 1000, 500	1000, 500	100 000, 100 000, 100 000	100 000, 100 000, 100 000, 100 000

TABLE 7. Values of π'.

		c_1	c_2			c_1	c_2
$(:, :, 1, 1)$	d_1	50	40	$(:, :, 2, 1)$	d_1	50	40
	d_2	40	50		d_2	40	50
	d_3	25	55		d_3	25	55
	d_4	40	40		d_4	40	40
		c_1	c_2			c_1	c_2
$(:, :, 1, 2)$	d_1	70	60	$(:, :, 2, 2)$	d_1	70	60
	d_2	40	80		d_2	40	80
	d_3	30	50		d_3	30	50
	d_4	40	50		d_4	40	50
		c_1	c_2			c_1	c_2
$(:, :, 1, 3)$	d_1	30	40	$(:, :, 2, 3)$	d_1	30	40
	d_2	50	60		d_2	50	60
	d_3	20	25		d_3	20	25
	d_4	45	55		d_4	45	55

TABLE 8. Values of π.

		d_1	d_2	d_3	d_4			d_1	d_2	d_3	d_4
$(:,:,1,1)$	f_1	50	40	60	30	$(:,:,2,2)$	f_1	70	60	40	25
	f_2	40	50	30	60		f_2	40	80	25	60
	f_3	25	55	45	35		f_3	30	50	55	45
		d_1	d_2	d_3	d_4			d_1	d_2	d_3	d_4
$(:,:,1,2)$	f_1	70	60	40	25	$(:,:,2,3)$	f_1	30	40	40	30
	f_2	40	80	25	60		f_2	50	60	70	50
	f_3	30	50	55	45		f_3	20	25	45	50
		d_1	d_2	d_3	d_4			d_1	d_2	d_3	d_4
$(:,:,1,3)$	f_1	30	40	40	30	$(:,:,3,1)$	f_1	50	40	60	30
	f_2	50	60	70	50		f_2	40	50	30	60
	f_3	20	25	45	50		f_3	25	55	45	35
		d_1	d_2	d_3	d_4			d_1	d_2	d_3	d_4
$(:,:,2,1)$	f_1	50	40	60	30	$(:,:,3,2)$	f_1	70	60	40	25
	f_2	40	50	30	60		f_2	40	80	25	60
	f_3	25	55	45	35		f_3	30	50	55	45
		d_1	d_2	d_3	d_4						
$(:,:,3,3)$	f_1	30	40	40	30						
	f_2	50	60	70	50						
	f_3	20	25	45	50						

TABLE 9. Computation experiments.

Case	Case type	Meta-heuristics				LINGO	
	$(F{-}V{-}D{-}V'{-}C{-}I)$	Algorithm	Solution	Generations	Computational time	Solution	Computational time
1	(3–3–4–2–2–3)	CRO	6.66×10^5	490	4.713 s	3.65×10^5	1800 s
		CROTS	5.28×10^5	339	3.308 s		
2	(5–4–6–3–3–4)	CRO	1.29×10^6	432	4.782 s	0.38×10^6	2110 s
		CROTS	0.95×10^6	394	4.295 s		
3	(8–5–9–4–5–5)	CRO	5.41×10^6	639	13.776 s	2.10×10^6	5106 s
		CROTS	3.86×10^6	565	12.180 s		
4	(3–6–4–5–10–7)	CRO	9.26×10^7	984	28.946 s	5.30×10^7	9856 s
		CROTS	7.37×10^7	795	27.020 s		
5	(5–8–6–7–15–12)	CRO	7.98×10^9	1262	43.896 s	2.36×10^9	15 556 s
		CROTS	4.54×10^9	1036	41.370 s		
6	(8–12–9–10–20–18)	CRO	5.78×10^{12}	1795	64.534 s	1.52×10^{12}	25 386 s
		CROTS	5.08×10^{12}	1632	60.152 s		
7	(3–18–4–16–30–25)	CRO	9.24×10^{16}	2367	79.216 s	6.28×10^{16}	39 408 s
		CROTS	8.07×10^{16}	2148	74.689 s		
8	(5–25–6–24–40–32)	CRO	3.96×10^{19}	3037	96.346 s	0.16×10^{19}	76 350 s
		CROTS	2.87×10^{19}	2861	93.380 s		
9	(8–32–9–30–50–40)	CRO	9.94×10^{24}	3972	119.376 s	7.68×10^{24}	115 354 s
		CROTS	9.01×10^{24}	3791	115.870 s		

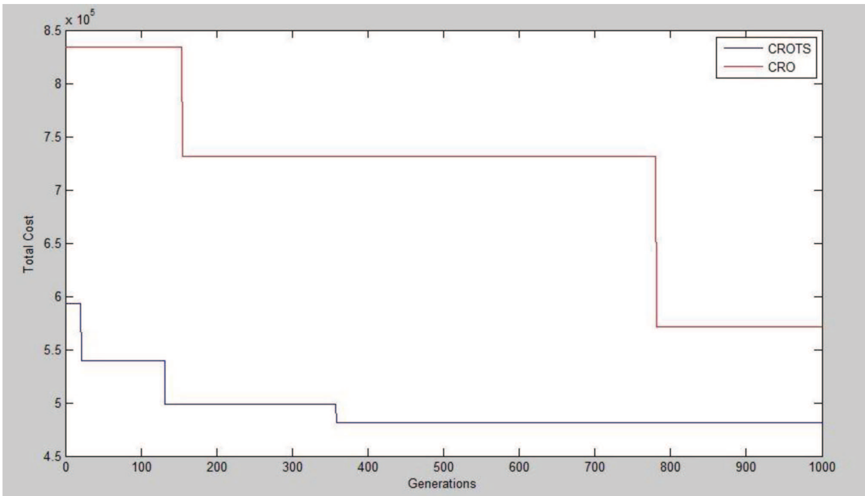

FIGURE 7. Convergence: case 1.

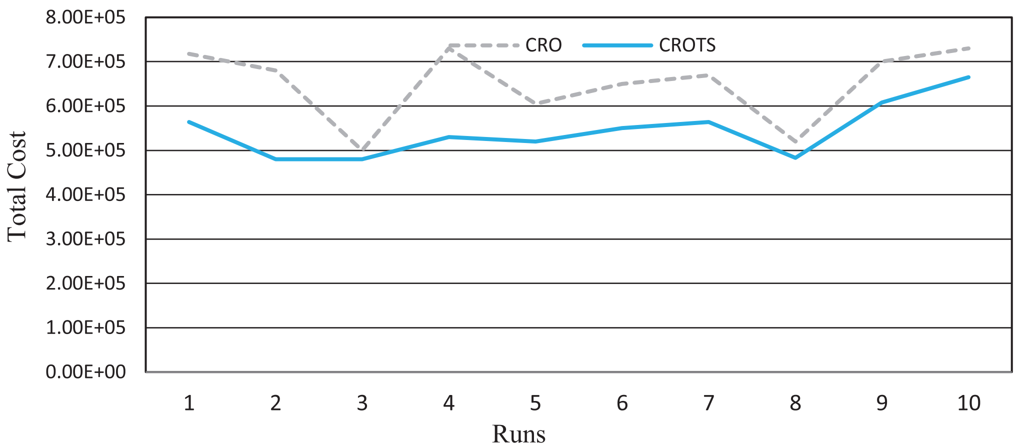

FIGURE 8. Graphical representation of result produced from 10 Runs of case 1.

From Table 9, it is observed that CROTS is showing a much faster convergence compared to basic CRO. It is also seen that CROTS is producing a much better optimal solution (higher solution quality), in a much lesser computational time, compared to CRO for all the 9 cases taken into consideration. For all the 9 cases, the overall cost produced by CROTS is much lesser compared to CRO. Hence, it can be clearly stated that CROTS is an algorithm of higher efficiency compared to basic CRO for the given problem. Hence, the overall transportation cost of the network is well reduced. To validate the suggested algorithms, the formulated model is solved by using an exact optimization approach in LINGO solver for all cases. There is a conflict between the exact optimization and meta-heuristics approaches; the exact optimization approach gives better results but takes too much computational time than the meta-heuristics, which is portrayed in the table of computational experiments.

The convergence graph for case 1 is given in Figure 7. The 10 runs of case 1 are depicted in the graphical representation given in Figure 8.

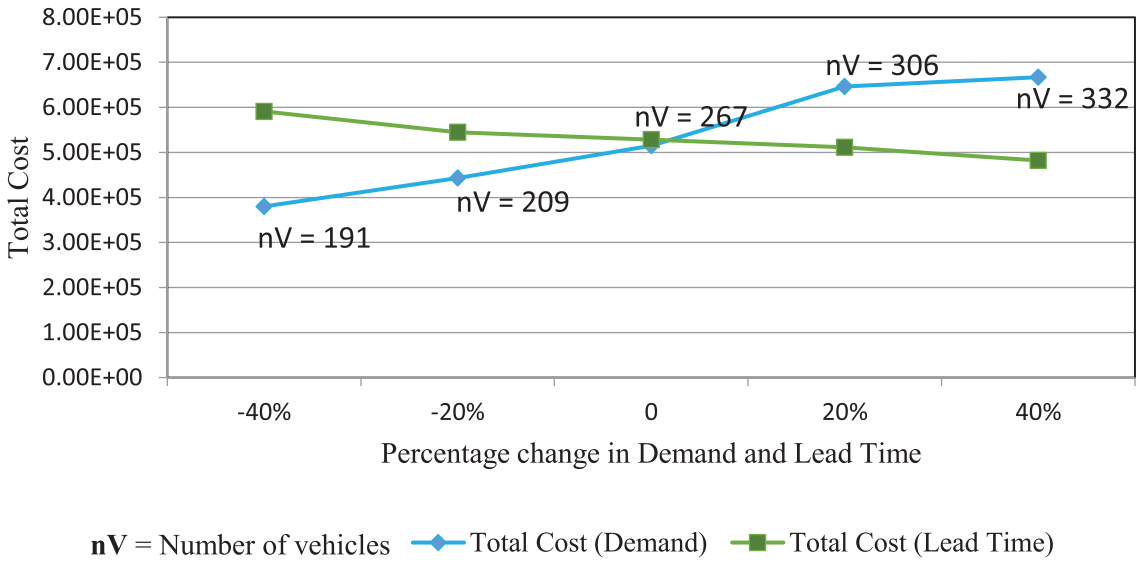

FIGURE 9. The effect of variation in Demand and Lead Time on the objective.

5.1. Sensitivity analysis

The sensitivity analysis was performed to evaluate the effect of certain model parameters on the overall cost objective. Different parameters such as $J_{ci}, \mathrm{LT}_c, €, \Psi, P, \pi_{fdvi}, \pi'_{dcv'i}, o_v, t_{v'}$ were considered for variations to evaluate their effect on the outcome.

5.1.1. The effects of demand and lead time

The demand and the lead time are varied by −40%, −20%, 20%, and 40% from their current values, and the corresponding changes produced in the overall cost objective are portrayed in Figure 9. Figure 9 shows that as the demand is increased and decreased by 40%, the overall cost rises and falls by 29.51% and 26.21% respectively. Similarly, when the lead time provided by the demand zones was increased and decreased by 40%, the overall cost was found to decrease and increase by 8.71% and 11.93% respectively. It was found that as demand increases, the total number of vehicles traveling in the SC also increases, which produces a rise in overall cost, as portrayed in Figure 9.

5.1.2. The influence of capacity of the vehicles

Each vehicle is provided with a fixed capacity. The sensitivity of the solution produced in terms of cost when the capacity of the vehicles is varied from −40% to +40% is shown in Figure 10. The figure shows a gradual decrease in the overall cost with a rise in the capacity of the vehicles. The transportation cost decreases due to the decrease in the number of vehicles required in transportation as the capacity increases, which is shown in Figure 10. As the capacity of the vehicle is varied by 40% above and below the current value, the overall cost is found to vary from a decrease of 20.89% to an increase of 59.33%.

5.1.3. The effects of the carbon tax and the transportation charge

The effect of variation in the carbon tax and the transportation charge is analyzed in this scenario. Both the parameters are increased and decreased by 40% from their initial values and the corresponding change in solution produced is represented by Figure 11. It is observed that with the increase in transportation charge from −40% to 40% of the current value, the overall cost displays a steady increase. A similar graph with different

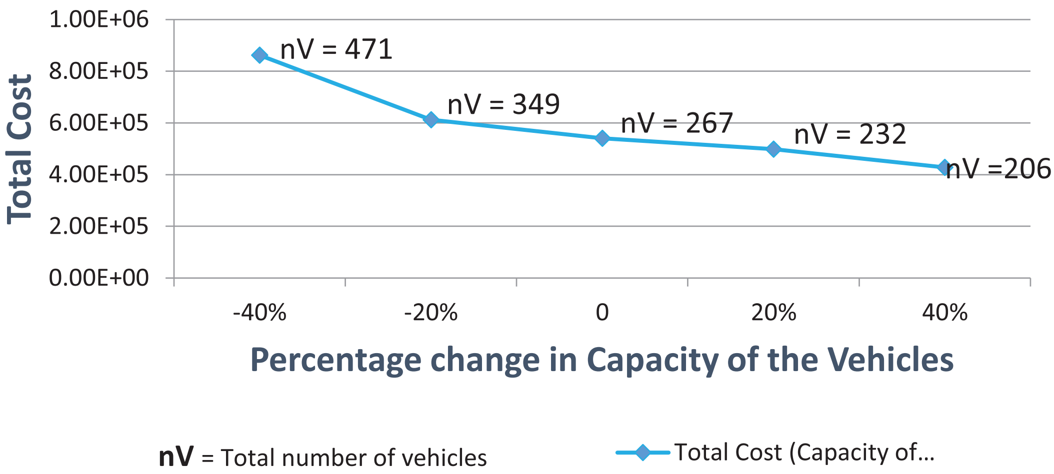

FIGURE 10. The effect of variation in the capacity of the vehicles on the objective.

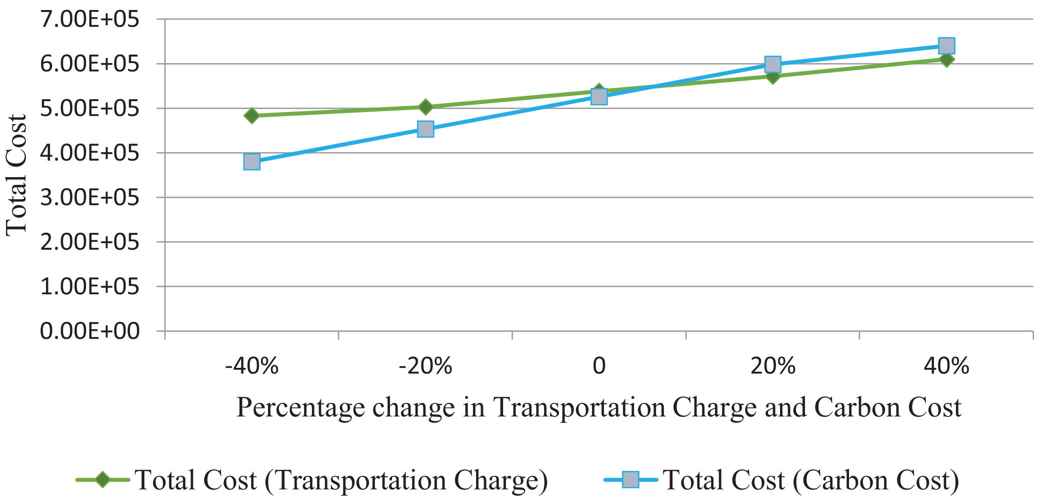

FIGURE 11. The effect of variation in Transportation Charge and Carbon Tax on objective.

values is obtained when the carbon tax is varied from −40% to 40% of its current value, producing a steady increase in overall cost produced.

5.2. Statistical analysis of algorithms

An independent 2 sample t-test is carried out in this section to perform the statistical analysis of the algorithms with 95% confidence for the first 3 cases only taken into consideration. The means of CRO and CROTS are compared by performing a hypothesis test and the hypothesis are taken as follows:

$$H_a : \mu_{\text{CROTS}} \geq \mu_{\text{CRO}}$$
$$H_b : \mu_{\text{CROTS}} < \mu_{\text{CRO}}.$$

It is detected from Table 10 that the P-values are less than 0.05 (commonly chosen value). It verifies that the overall cost attained from the CRO algorithm is greater than the overall cost generated by the CROTS

TABLE 10. Result obtained from the statistical analysis of the 3 cases.

Problem size	Algorithm	N	Mean	SD	t-value	P-value
(3–3–4–2–2–3)	CROTS	11	549 072	48 492	−7.1443	0.00000086
	CRO	11	681 600	37 863		
(5–4–6–3–3–4)	CROTS	11	1 006 227	141 954	−5.7594	0.00001232
	CRO	11	1 337 545	127 479		
(8–5–9–4–5–5)	CROTS	11	3 168 236	587 587	−5.6308	0.00002422
	CRO	11	4 864 252	807 907		

algorithm. Hence, it can be clearly stated that CROTS shows better performance over CRO algorithm. The solutions obtained from the statistical analysis only for 3 cases are written in Table 10.

5.3. Managerial implications and insights

The effectiveness and the efficiency of transportation in the current transportation network can be improved using a few of the management implications that we obtained during the study. The capacity of the vehicles plays a very important role as far as the overall cost incurred is concerned. The vehicles of a wide range of capacities starting from a large to sufficiently smaller capacities can be provided at the factories and the DCs which will help to significantly reduce the cost incurred for transportation operation in e-commerce. The studies also throw light into the importance of lead times provided by the demand zones as far as the cost is considered. The speed of travel of each vehicle is found to be dependent on the lead time provided by the demand zones. By striking an efficient trade-off between the lead time provided by each demand zone and the speed of travel of each vehicle, the cost due to emission can be controlled, thereby producing a significant drop in the overall costs.

These managerial insights obtained can be used for effective decision-making in a transportation network design for an e-commerce platform. The solutions from the current study are very helpful in deciding the distance between different centers in the SC and the corresponding transportation charges. It also helps to decide the capacity of different vehicles that should be employed for transportation of materials from factories as well as the DCs. This study depicts the relation between lead time and the overall cost. This helps in negotiating with the demand zones to provide sufficient lead times for the procurement of materials under demand. Hence the insights obtained from the study if used properly can help in efficient decision making for the design of an SC network.

6. CONCLUSION

In this study, a multi-vehicle, multi-product sustainable transportation network related to an e-commerce platform is investigated. A mixed-integer-non-linear-programming model is formulated to capture the problems in the sustainable SC network. The objective function minimizes the overall cost associated with transportation in a network. A hybrid CRO algorithm with Tabu Search has been suggested to solve the formulated model. The Tabu Search operator introduced more intensification into the solution space by performing the neighborhood search operation, thereby improving the solution quality and performance of the algorithm. The algorithms were used for solving 9 different cases of the problem. From the computational solutions, it is detected that the hybrid algorithm is providing better solution quality, in less computational time, for each of the 9 cases considered. The LINGO gives better results but takes too much than the meta-heuristics, which are clearly portrayed in Table 9.

For future research, this model can be combined with the inventory management problem. A probabilistic environment based on stochastic demand can also be embedded into the model. The reliability factor can be introduced to reduce the risk of facility disruption. Further, the hybrid algorithm introduced could be used for solving multi-objective optimization and scheduling problems.

References

[1] R. Abyazi-Sani and R. Ghanbari, An efficient tabu search for solving the uncapacitated single allocation hub location problem. *Comput. Ind. Eng.* **93** (2016) 99–109.

[2] A. Anderluh, P.C. Nolz, V.C. Hemmelmayr and T.G. Crainic, Multi-objective optimization of a two-echelon vehicle routing problem with vehicle synchronization and "grey zone" customers arising in urban logistics. *Eur. J. Oper. Res.* **289** (2021) 940–958.

[3] M.S. Atabaki, A.A. Khamseh and M. Mohammadi, A priority-based firefly algorithm for network design of a closed-loop supply chain with price-sensitive demand. *Comput. Ind. Eng.* **135** (2019) 814–837.

[4] C. Claycomb, K. Iyer and R. Germain, Predicting the level of B2B e-commerce in industrial organizations. *Ind. Mark. Manag.* **34** (2005) 221–234.

[5] J.F. Cordeau, M. Gendreau and G. Laporte, A tabu search heuristic for periodic and multi-depot vehicle routing problems. *Networks* **30** (1997) 105–119.

[6] T.L. Dam, K. Li and P. Fournier-Viger, Chemical reaction optimization with unified tabu search for the vehicle routing problem. *Soft Comput.* **21** (2017) 6421–6433.

[7] A. Dwivedi, A. Jha, D. Prajapati, N. Sreenu and S. Pratap, Meta-heuristic algorithms for solving the sustainable agro-food grain supply chain network design problem. *Mod. Supply Chain Res. Appl.* (2020). DOI: 10.1108/MSCRA-04-2020-0007.

[8] S. Elhedhli and R. Merrick, Green supply chain network design to reduce carbon emissions. *Transp. Res. Part D Transp. Environ.* **17** (2012) 370–379.

[9] B. Fahimnia, J. Sarkis, F. Dehghanian, N. Banihashemi and S. Rahman, The impact of carbon pricing on a closed-loop supply chain: an Australian case study. *J. Clean. Prod.* **59** (2013) 210–225.

[10] J. Hong, A. Diabat, V.V. Panicker and S. Rajagopalan, A two-stage supply chain problem with fixed costs: an ant colony optimization approach. *Int. J. Prod. Econ.* **204** (2018) 214–226.

[11] A.Y.S. Lam and V.O.K. Li, Chemical-reaction-inspired metaheuristic for optimization. *IEEE Trans. Evol. Comput.* **14** (2009) 381–399.

[12] A.Y.S. Lam, V.O.K. Li and J.J.Q. Yu, Real-coded chemical reaction optimization. *IEEE Trans. Evol. Comput.* **16** (2012) 339–353.

[13] K.H. Leung, C.K.M. Lee and K.L. Choy, An integrated online pick-to-sort order batching approach for managing frequent arrivals of B2B e-commerce orders under both fixed and variable time-window batching. *Adv. Eng. Inf.* **45** (2020) 101125.

[14] J. Li and Q. Pan, Chemical-reaction optimization for solving fuzzy job-shop scheduling problem with flexible maintenance activities. *Int. J. Prod. Econ.* **145** (2013) 4–17.

[15] W.C. Ling, A.B. Verasingham, V. Andiappan, Y.K. Wan, I.M.L. Chew and D.K.S. Ng, An integrated mathematical optimisation approach to synthesise and analyse a bioelectricity supply chain network. *Energy* **178** (2019) 554–571.

[16] I. Mallidis, R. Dekker and D. Vlachos, The impact of greening on supply chain design and cost: a case for a developing region. *J. Transp. Geogr.* **22** (2012) 118–128.

[17] D.G. Mogale, S.K. Kumar, F.P.G. Marquez and M.K. Tiwari, Bulk wheat transportation and storage problem of public distribution system. *Comput. Ind. Eng.* **104** (2017) 80–97.

[18] F. Mohebalizadehgashti, H. Zolfagharinia and S.H. Amin, Designing a green meat supply chain network: a multi-objective approach. *Int. J. Prod. Econ.* **219** (2020) 312–327.

[19] R. Ngambusabongsopa, Z. Li and E. Eldesouky, A hybrid mutation chemical reaction optimization algorithm for global numerical optimization. *Math. Probl. Eng.* **2015** (2015). DOI: 10.1155/2015/375902.

[20] T.T. Nguyen, Z. Li, S. Zhang and T.K. Truong, A hybrid algorithm based on particle swarm and chemical reaction optimization. *Expert Syst. Appl.* **41** (2014) 2134–2143.

[21] F.R. Nilsson, A complexity perspective on logistics management: rethinking assumptions for the sustainability era. *Int. J. Logist. Manag.* **30** (2019) 681–698.

[22] J. Noh and J.S. Kim, Cooperative green supply chain management with greenhouse gas emissions and fuzzy demand. *J. Clean. Prod.* **208** (2019) 1421–1435.

[23] I. Nouira, R. Hammami, Y. Frein and C. Temponi, Design of forward supply chains: impact of a carbon emissions-sensitive demand. *Int. J. Prod. Econ.* **173** (2016) 80–98.

[24] T. Paksoy, T. Bektaş and E. Özceylan, Operational and environmental performance measures in a multi-product closed-loop supply chain. *Transp. Res. Part E Logist. Transp. Rev.* **47** (2011) 532–546.

[25] D. Prajapati, F. Zhou, N. Cheikhrouhou and S. Pratap, Minimizes the time window for delivery of orders in B2B e-commerce. In: Proceedings of the 5th International Conference on Industrial Engineering (ICIE). Sochi, Russia (2019) 18–19.

[26] D. Prajapati, A.R. Harish, Y. Daultani, H. Singh and S. Pratap, A clustering based routing heuristic for last-mile logistics in fresh food e-Commerce. *Glob. Bus. Rev.* (2020). DOI: 10.1177/0972150919889797.

[27] D. Prajapati, F. Zhou, M. Zhang, H. Chelladurai and S. Pratap, Sustainable logistics network design for multi-products delivery operations in B2B e-commerce platform. *Sādhanā* **46** (2021) 1–13.

[28] A. Ramudhin, A. Chaabane, M. Kharoune and M. Paquet, Carbon market sensitive green supply chain network design. *2008 IEEE Int. Conf. Ind. Eng. Eng. Manag.* **5** (2008) 1093–1097.

[29] H.S. Rao, Reducing carbon emissions from transport projects. *Eval. Knowl. Br.* **16** (2010) 1–96.

[30] Scenario Building Team, Long term mitigation scenarios: strategic options for South Africa. *Long Term Mitig. Scenar. Scenar. Doc. Deaprtment Environ. Tour.* (2007) 34. http://hdl.handle.net/11427/16804.

[31] A. Shamsuzzoha, E. Ndzibah and K. Kettunen, Data-driven sustainable supply chain through centralized logistics network: case study in a Finnish pharmaceutical distributor company. *Curr. Res. Environ. Sustain.* **2** (2020) 100013.

[32] K. Shaw, M. Irfan, R. Shankar and S.S. Yadav, Low carbon chance constrained supply chain network design problem: a benders decomposition based approach. *Comput. Ind. Eng.* **98** (2016) 483–497.

[33] M. Sreenivas and T. Srinivas,, The Role of Transportation in Logistics Chain. Alluri Institute of Management Science, Warangal. AP India (1814) 1–10.

[34] S.K. Srivastava, Green supply-chain management: a state-of-the-art literature review. *Int. J. Manag. Rev.* **9** (2007) 53–80.

[35] A. Stefaniec, K. Hosseini, J. Xie and Y. Li, Sustainability assessment of inland transportation in China: a triple bottom line-based network DEA approach. *Transp. Res. Part D Transp. Environ.* **80** (2020) 102258.

[36] Y. Tan, Y. Shi, F. Buarque, A. Gelbukh, S. Das and A. Engelbrecht, Advances in swarm and computational intelligence. In: 6th International Conference, ICSI 2015 held in conjunction with the Second BRICS Congress, CCI 2015 Beijing, China, June 25–28, 2015 Proceedings, Part II. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinf.)*. Vol. 9141 (2015) 229–237.

[37] J. Tang, H. Heinimann, K. Han, H. Luo and B. Zhong, Evaluating resilience in urban transportation systems for sustainability: a systems-based Bayesian network model. *Transp. Res. Part C Emerg. Technol.* **121** (2020) 102840.

[38] P. Taylor, V.V. Panicker, R. Vanga and R. Sridharan, Ant colony optimisation algorithm for distribution-allocation problem in a two-stage supply chain with a fixed transportation charge. *Int. J. Prod. Res.* **51** (2013) 698–717.

[39] C.J. Vidal and M. Goetschalckx, Strategic production-distribution models: a critical review with emphasis on global supply chain models. *Eur. J. Oper. Res.* **98** (1997) 1–18.

[40] Y. Wang, Y. Sun, X. Guan and Y. Guo, Two-echelon location-routing problem with time windows and transportation resource sharing. *J. Adv. Transp.* **2021** (2021). DOI: 10.1155/2021/8280686.

[41] S.X. Xu, M. Cheng and G.Q. Huang, Efficient intermodal transportation auctions for B2B e-commerce logistics with transaction costs. *Transp. Res. Part B* **80** (2020) 322–337.

[42] P. Yang and L. Zeng, Models and methods for two-echelon location routing problem with time constraints in city logistics. *Math. Probl. Eng.* **2018** (2018). DOI: 10.1155/2018/2549713.

[43] M. Zhang, S. Pratap, G.Q. Huang and Z. Zhao, Optimal collaborative transportation service trading in B2B e-commerce logistics. *Int. J. Prod. Res.* **7543** (2017) 1–17.

[44] M. Zhang, L. Chen and X. Chen, An advanced chemical reaction optimization algorithm based on balanced local and global search. *Math. Prob. Eng.* **2018** (2018). DOI: 10.1155/2018/8042689.

[45] M. Zhang, S. Pratap, Z. Zhao, D. Prajapati and G.Q. Huang, Forward and reverse logistics vehicle routing problems with time horizons in B2C e-commerce logistics. *Int. J. Prod. Res.* **59** (2021) 6291–6310.