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Evolutionary algorithm based approach for solving transportation problems in normal and pandemic scenario

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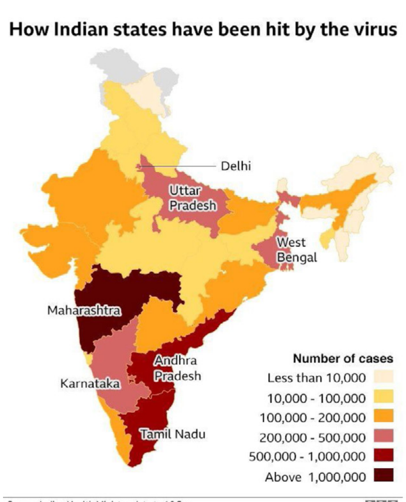
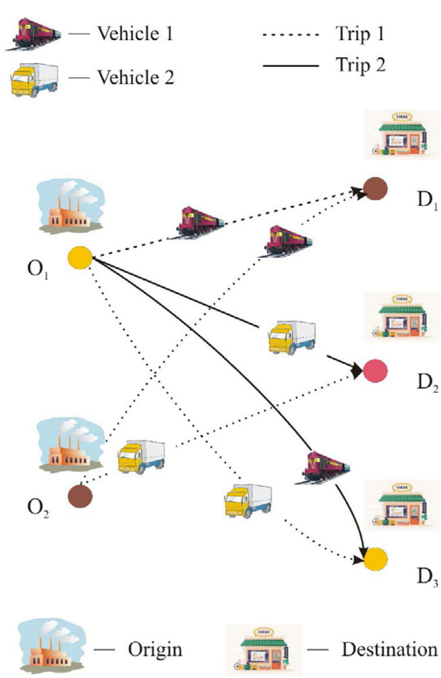
GRAPHICAL ABSTRACT

Let in a Pandemic scenario such as COVID-19, regions are categorized in different groups based on degree of severity of restrictive measures taken in a region. In a Pandemic scenario, given a transportation network consisting of m origins and n destinations, in which multiple vehicles with different capacities available at each origin are allowed to take multiple trips, the aim of the problem is to obtain minimum cost transportation plan with least number of trips of vehicles in between regions with higher restrictions, and to analyze the effect of reduced number of trips of vehicles in between regions with higher restrictions on the transportation cost for the transportation problem in Pandemic scenario with an upper limit on transportation cost as a constraint compared to the same transportation problem without any such constraint and an equivalent transportation in normal scenario.



Categorization of Indian states in 6 different groups based on the number of active cases of COVID-19.



A diagrammatic representation of a solution of the transportation problem in Pandemic scenario.

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ABSTRACT

In recent times, COVID-19 pandemic has posed certain challenges to transportation companies due to the restrictions imposed by different countries during the lockdown. These restrictions cause delay and/ or reduction in the number of trips of vehicles, especially, to the regions with higher restrictions. In a pandemic scenario, regions are categorized into different groups based on the levels of restrictions imposed on the movement of vehicles based on the number of active cases (i.e., number of people infected by COVID-19), number of deaths, population, number of COVID-19 hospitals, etc. The aim of this study is to formulate and solve a fixed-charge transportation problem (FCTP) during this pandemic scenario and to obtain transportation scheme with minimum transportation cost in minimum number of trips of vehicles moving between regions with higher levels of restrictions. For this, a penalty is imposed in the objective function based on the category of the region(s) where the origin and destination are situated. However, reduction in the number of trips of vehicles may increase the transportation cost to unrealistic bounds and so, to keep the transportation cost within limits, a constraint is imposed on the proposed model. To solve the problem, the Genetic Algorithm (GA) has been modified accordingly. For this purpose, we have designed a new crossover operator and a new mutation operator to handle multiple trips and capacity constraints of vehicles. For numerical illustration, in this study, we have solved five example problems considering three levels of restrictions, for which the datasets are generated artificially. To show the effectiveness of the constraint imposed for reducing the transportation cost, the same example problems are then solved without the constraint and the results are analyzed. A comparison of results with existing algorithms proves that our algorithm is effective. Finally, some future research directions are discussed.

1. Introduction

Transportation problem is an important problem in operations research, since it is directly linked with the economy of a country and inflation. It is one of the most studied problem due to its applications in wide field of topics, which includes transportation network, supply chain and logistics, manufacturing industries, location routing, etc. The first model of transportation network was developed by Hitchcock [1] in 1941, which is known as the classical transportation problem (CTP). Since CTP belongs to the class of linear programming problem, it is solvable in polynomial time. Many researchers developed exact and approximate algorithms to solve such kind of problems. Some of the earliest works on transportation and its associated problems are reported in [2–5]. To make the transportation problem (TP) more realistic, Hirsch and Dantzig [6] incorporated fixed cost into the transportation problem (TP), and named the resulting problem as the fixed-charge transportation problem (FCTP). A FCTP considers the involvement of two types of costs, variable cost and fixed cost. The variable cost depends on the quantity of an item to be transported, whereas the fixed cost is incurred for a route being used and is independent of the quantity of item. Some examples of fixed cost may include toll tax on highways, docking charge at ports, warehouse setup cost, etc. Later, Balinski [7] formulated the FCTP mathematically. The inclusion of fixed cost result in discontinuities in the objective function and consequently, makes the problem complex. Moreover, the FCTP is NP-hard [8,9] and cannot be solved by the traditional algorithms used to solve TPs. The FCTP is thus a classic example of a combinatorial optimization problem. In the last decade or so, researchers mainly focused on approximate methods (heuristics and metaheuristics) to solve the FCTP and its variants due to less computational time over the existing exact methods. Gen et al. [10] adopted the spanning tree representation into the Genetic Algorithm, which they named spanning tree-based Genetic Algorithm (st-GA), to solve the FCTP. Then, the algorithm is extended for the bicriteria FCTP. The result shows better performance of the st-GA than the matrix-based GA with respect to computational time. Hajiaghaei-Keshteli [8] used the Prüfer number representation with certain modifications to design a GA based on spanning tree that overcome the limitations of some earlier works [10,11]. The major advantage of this method is that, it guarantees the generation of feasible chromosomes only unlike the aforementioned works. Molla-Alizadeh-Zavardehi [12] modeled a cost minimizing capacitated fixed-charge transportation problem for a two-stage supply chain network, in which some locations are to be selected as distribution centers to transport different quantities of an item to customers. Then, they used two algorithms, namely, Genetic Algorithm (GA) and Artificial Immune Algorithm (AIA) to solve the NP-hard problem. A comparison of the results obtained show better performance of AIA over GA in terms of both, the solution quality and the robustness, especially for large size problems. Xie and Jia [13] formulated a FCTP with the variable cost in the quadratic form (nonlinear FCTP, in short NFCTP). Due to non-linearity, NFCTP is more difficult to solve than the FCTP. To better absorb the non-linear structure of NFCTP, a hybrid genetic algorithm named NFCTP-HGA is developed that uses minimum cost flow algorithm as decoder. Numerical experiments proved better performance of the algorithm with respect to computational time, memory usage, efficiency and robustness. Lofti & Tavakkoli-Moghaddam [14] adapted the GA with a priority based encoding, which is a modified version of the priority based encoding proposed by Gen et al. [15] to adapt with the FCTP structure. Balaji et al. [16] formulated a truck load constraints (FCT-TLC) problem, a special case of the FCTP, in which it is assumed that the quantity of items to be transported from an origin exceed the capacity of the vehicle, and consequently, may require more than one trip to transport the whole quantity. The FCT-TLC is then solved using two algorithms, namely, Genetic Algorithm (GA) and Simulated Annealing (SA). Computational results performed on twenty test examples shows that SA produces the same or better quality solutions than GA.

Some researchers also considered two or more of cost, transport time, profit, etc. as objectives that are conflicting in nature and posed the FCTP as multi-objective optimization problem. Biswas et al. [17] formulated a solid multi-objective FCTP with non-linear cost function. The uncertainties in some parameters are also considered in the form of interval numbers, and an equivalent formulation of the problem is presented in interval environment. Then, suitable genetic operators are developed, and incorporated into the non-dominated sorting genetic algorithm-II (NSGA-II) [18] to solve the problem in crisp environment. The FCTP with interval objectives is solved using an extended NSGA-II to cope with interval objectives. Numerical experiments are performed and the results are compared with another metaheuristic SPEA2 (Strength Pareto Evolutionary Algorithm 2), implementing the same genetic operators. Roy et al. [19] modeled a multi-objective FCTP considering the parameters of objective functions to be random rough variables and the parameters corresponding to demand and supply to be rough variables. The problem is first converted into a deterministic form using an expected value operator, and is then solved using three different procedures, namely, the fuzzy programming, global criterion and ε-constrained method. The result shows the better performance of ε-constrained method over other methods. Midya and Roy [20] considered a multi-objective FCTP (named as MOFCTP), in which all the parameters are taken to be imprecise and measured using rough intervals. The MOFCTP is converted into deterministic form using rough programming and is then solved using two methods, namely, fuzzy programming method and linear weighted sum method. A comparison of results show better performance of the linear weighted sum method. Ghosh et al. [21] formulated a multi-objective solid FCTP (named as MOFCSTP) considering all the parameters and variables as triangular intuitionistic fuzzy numbers (TIFNs) having membership and non-membership function. The modeled MOFCSTP is first reduced to an interval-valued intuitionistic fuzzy transportation problem (IVIFTP) using (α, β)-cut, and then into an equivalent crisp problem using an accuracy function. Then, the crisp problem is solved using the methods fuzzy programming (FP), intuitionistic fuzzy programming (IFP) and goal programming (GP). The results show that IFP performs best among the applied methods. Biswas and Pal [22] formulated a multi-objective solid FCTP, considering fixed capacities of modes of transport that are different for each mode. New genetic operators (crossover and mutation) are designed to deal with the capacity constraint. The problem is then solved using a modified NSGA-II, obtained by incorporating the genetic operators. Some numerical examples are solved using the modified NSGA-II and the results are compared with two other metaheuristics on the basis of various performance metrics, which indicates towards the overall supremacy of the modified NSGA-II.

In recent years, researchers solved different variants of FCTP considering multiple items [23–25], multiple vehicles/conveyances [17,26–28] and capacity constraints of conveyances (modes of transport) [12,22]. Some researchers also considered the uncertainties of different parameters and measured the uncertainties using interval [17,29], fuzzy [23,30,31], rough [19] and fuzzy-rough [31].

Recently, due to the COVID-19 pandemic, interests are growing among researchers to adapt different network models such as manufacturing industry, supply chain, transportation and logistics for the changed scenario. Amankwah-Amoah [32] presented a conceptual framework of business firm's responses due to restrictions imposed in business activities in the ongoing COVID-19 pandemic. Then, considering the global airline industry as case study, different strategic responses such as changes in in-flight service, flight cancellations, pursue emergency aids and financial supports are analyzed, which provide few outlines for the service providers for recovery. Mogaji [33] studied the impact of COVID-19 over a long period on transportation in Lagos State of Nigeria, where the restrictions are difficult to maintain considering practical scenarios. Then, some feasible strategies are outlined based on 'avoid-shift-improve' for the policymakers, both in private and public sectors. The time lag between recognizing a problem and the time of activation of a policy on a system is studied by Bian et al. [34]. A detection process is developed computing the change point using likelihood ratio, regression value and a Bayesian change point detection method. Then, as a case study, two cities of U. S. are investigated which reveal that the nation-wide declaration of emergency has no impact on policy lag, while the two policies 'stay-at-home' and 'reopening' has certain lead effect. In addition to these, some works on supply chains and logistics in COVID-19 pandemic includes that given in [35–43], respectively.

1.1. Motivation

From the literature survey, it is evident that most countries imposed restrictions which greatly affect the transportation system of items (both essential and non-essential). Thus, the existing models of transportation problem (TP) are based on the assumption that there is no such restrictions in the movement of vehicles and suitable for normal scenario only. Moreover, in most of the works on TP (in particular fixed-charge transportation problem (FCTP)), it is considered that a vehicle can avail at most one trip to a destination. However, in real-world scenario, the amount of an item available at an origin may exceed the total capacity of all the vehicles, and hence, one or more vehicles may need more than one trip to satisfy the demand at a destination. In the existing works, none of the researchers has considered that the number of trips of a vehicle to a destination can be more than one, except Balaji et al. [16]. However, the number of trips of a vehicle to a destination can be more than one, and must be considered into the formulation, since for a FCTP, the number of trips contribute to the fixed cost, total time and total profit (in case of shipping of perishable items).

In pandemic scenario, regions are categorized in different groups depending upon the level of restriction in a region persistent over a certain period of time. The level of restriction in a region is dependent on various factors such as number of active cases (i.e., number of people infected), number of deaths, population density, number of COVID-19 hospitals and number of migrant workers returned or might return to a region. Thus, in pandemic scenario, for origins and destinations that are situated in regions with higher restrictions, the number of trips of vehicles need to be reduced in such a way that, a balance between the supply and demand of item(s) is maintained. However, reducing the number of trips of vehicles may increase the transportation cost to an unrealistic bound. Thus, a transportation company needs to find a proper balance between the transportation cost and the reduction in number of trips of vehicles considering the levels of restriction imposed in different regions. Hence, planning of transportation scheme in a pandemic scenario is a challenging task for transportation companies, and consideration of a new type of transportation plan becomes necessary. However, there is no such work available in the literature, which motivated us to formulate a transportation model for pandemic scenario and to solve it. This model is also applicable in emergency scenarios such as major earthquakes, floods and other natural calamities in which only a limited number of trips of some particular types of vehicles can be availed.

1.2. Our proposed contribution

In this paper, we first formulate a fixed cost transportation model for a homogeneous item in COVID-19 pandemic scenario, in which regions are categorized in groups depending upon the level of restrictions on the mobility of freight vehicles. It is also considered that more than one type of vehicles are available at each origin, and each vehicle may take more than one trip to the same or different destinations, where the capacity of each vehicle is not the same. For an origin and a destination, the variable cost of a unit item and the fixed-charge varies for each vehicle, which also varies for different pairs of an origin and a destination. The aim of the problem is to obtain a minimum cost transportation plan with minimum number of trips of vehicles moving from origins to destinations that are situated in regions with higher levels of restrictions. For this, the problem is posed as a single-objective optimization problem (SOOP), in which minimization of transportation cost is considered as the objective function. Moreover, to minimize the number of trips of vehicles from origins to destinations situated in regions with higher levels of restrictions, a penalty is imposed in the objective function for each trip of a vehicle that depends upon the level of restrictions of the two regions. To keep the transportation cost within realistic bound, a constraint is imposed with an upper bound on transportation cost. Then, the problem is solved using a Genetic Algorithm (GA) based approach, in which newly designed genetic operators (crossover and mutation) are incorporated to handle multiple trips and capacity constraints of vehicles. Some numerical examples of the proposed model are generated artificially, in which three levels of restrictions are considered for the regions associated with the origins and destinations. To prove that the imposed constraint plays a crucial role, the same examples are solved without considering the constraint. Thereafter, the same examples are solved in normal scenario, i.e., ignoring any categorization of regions and the results are analyzed. The performance of our algorithm is also compared with three existing works, considering a particular instance of our proposed FCTP model. Finally, some future research directions are discussed.

The organization of the rest of the paper is as follows. In Section 2, the notations and abbreviations are presented. The mathematical model of the FCTP in pandemic scenario is given in Section 3. The solution methodology is discussed in Section 4. Section 5 contains the experimental results with discussion. Finally, in Section 6, conclusions are drawn with the lines of further research directions are discussed.

2. Notations

The notations used to formulate and to solve the problem are the following.

X_0	: Size of initial population
It_{max}	: Maximum number of iterations (Termination criterion)
p_{cros}	: Crossover probability
p_{mut}	: Mutation probability
$\{O_1, O_2, \ldots, O_m\}$	: Set of m origins
$\{D_1, D_2, \ldots, D_n\}$	: Set of n destinations
$\{V_1, V_2, \ldots, V_l\}$	: Set of l vehicles available at each origin
a_λ	: Quantity of the item available at origin $O_\lambda (\lambda = 1, 2, \ldots, m)$
b_μ	: Demand of the item at destination D_μ $(\mu = 1, 2, \ldots, n)$
e_η	: Capacity of vehicle V_η $(\eta = 1, 2, \ldots, l)$
$c_{\lambda\mu\eta}$	: Variable transportation cost per unit of item from an origin O_λ to a destination D_μ by a vehicle V_η
$h_{\lambda\mu\eta}$	: Fixed-charge incurred for transportation of a positive quantity of the item from an origin O_λ to a destination D_μ using a vehicle V_η
$x_{\lambda\mu\eta u}$	: Decision variable denoting unknown quantity of the item to be transported from origin O_λ to a destination D_μ in uth trip of a vehicle V_η
$f\left(x_{\lambda\mu\eta u}\right)$	: Total transportation cost in transportation of $x_{\lambda\mu\eta u}$ units of the item from an origin O_λ to a destination D_μ in uth trip of a vehicle V_η
$N_\eta^\lambda(x)$	: Number of trips taken by the vehicle V_η from origin O_λ corresponding to the chromosome/solution $\left(x_{\lambda\mu\eta u}\right)$
$g_{\lambda\mu\eta u}$	: A Boolean variable, which takes the value 1, if a positive quantity of the item is transported in uth trip of the vehicle V_η from origin O_λ to destination D_μ, otherwise it takes the value 0.
L_U	: Upper limit on transportation cost

List of abbreviations:

Abbreviation	Explanation
TP	Transportation problem
CTP	Classical transportation problem
FCTP	Fixed-charge transportation problem
SOOP	Single objective optimization problem
MOOP	Multi-objective optimization problem
GA	Genetic algorithm
NSGA-II	Non-dominated sorting genetic algorithm-II
LSR	Level of Severity of Restriction
NP-hard	Non-deterministic polynomial-time hard
SPEA2	Strength Pareto Evolutionary Algorithm 2

3. Mathematical formulation of a FCTP in pandemic scenario

In this section, we present the mathematical formulations of a FCTP in pandemic scenario. In this model, we consider the FCTP to be balanced, since, to solve an unbalanced FCTP, it is first converted into a balanced one. In case of a balanced FCTP, the sum of availabilities of the item at all the origins is equal to the sum of demands of the item at all the destinations, i.e., $\sum_{\lambda=1}^{m} a_\lambda = \sum_{\mu=1}^{n} b_\mu$.

3.1. Fixed-charge transportation problem in pandemic scenario

Consider a transportation network consisting of m origins, say, $O_1, O_2, \ldots, O_m$ and n destinations, say, $D_1, D_2, \ldots, D_n$. Let in COVID-19 pandemic, the regions associated with the origins and destinations be divided in K categories, say, $G_1, G_2, \ldots, G_K$, arranged in increasing order of levels of restrictions. Let there be l types of vehicles available at each origin, where each vehicle may take one or more trips to same or different destinations and the capacity of each vehicle being different. The unit variable cost $c_{\lambda\mu\eta}$

of the item and the fixed cost $h_{\lambda\mu\eta}$ corresponding to the vehicle V_η to transport from origin O_λ to destination D_μ vary for different pairs of origins and destinations. Let for a trip of a vehicle from an origin O_λ to a destination D_μ situated in regions G_r and G_s, respectively, let P_{rs} be the penalty to be imposed on the objective function. The penalty P_{rs} depends only on the level of restrictions in the two regions G_r and G_s, i.e., the penalty is large if the level of restrictions is high and vice-versa. A higher value of penalty will restrict the vehicles to take less number of trips between an origin and a destination.

$$\text{Minimize } Z = \underbrace{\sum_{\lambda=1}^{m}\sum_{\mu=1}^{n}\sum_{\eta=1}^{l}\sum_{u=1}^{N_\eta^\lambda} f\left(x_{\lambda\mu\eta u}\right)}_{\text{Total transportation cost}} + \sum_{\lambda=1}^{m}\sum_{\mu=1}^{n}\sum_{\eta=1}^{l}\sum_{u=1}^{N_\eta^\lambda} P_{rs}.g_{\lambda\mu\eta u} \tag{1}$$

subject to

$$\text{subject to } \sum_{\mu=1}^{n}\sum_{\eta=1}^{l}\sum_{u=1}^{N_\eta^\lambda} x_{\lambda\mu\eta u} \leq a_\lambda;\ \lambda = 1, 2, \ldots, m \tag{2}$$

$$\sum_{\lambda=1}^{m}\sum_{\eta=1}^{l}\sum_{u=1}^{N_\eta^\lambda} x_{\lambda\mu\eta u} \geq b_\mu;\ \mu = 1, 2, \ldots, n \tag{3}$$

$$x_{\lambda\mu\eta u} \leq e_\eta;\ \lambda = 1, 2, \ldots, m;$$
$$\mu = 1, 2, \ldots, n;\ \eta = 1, 2, \ldots, l;\ u = 1, 2, \ldots, N_\eta^\lambda \tag{4}$$

$$\sum_{\lambda=1}^{m} a_\lambda = \sum_{\mu=1}^{n} b_\mu \tag{5}$$

$$\text{and } x_{\lambda\mu\eta u} \geq 0;\ \lambda = 1, 2, \ldots, m;$$
$$\mu = 1, 2, \ldots, n;\ \eta = 1, 2, \ldots, l;\ u = 1, 2, \ldots, N_\eta^\lambda \tag{6}$$

Here, $f\left(x_{\lambda\mu\eta u}\right)$ represents the total transportation cost (the sum of the total variable cost and the total fixed-charge) associated with the transportation of $x_{\lambda\mu\eta u}$ units of the item from origin O_λ to destination D_μ in trip u of the vehicle V_η, and is given by $f\left(x_{\lambda\mu\eta u}\right) = c_{\lambda\mu\eta}.x_{\lambda\mu\eta u} + h_{\lambda\mu\eta}.g_{\lambda\mu\eta u}$ for the linear form of FCTP, and $f\left(x_{\lambda\mu\eta u}\right) = c_{\lambda\mu\eta}.x^2_{\lambda\mu\eta u} + h_{\lambda\mu\eta}.g_{\lambda\mu\eta u}$ for the quadratic form of FCTP (non-linear). From here on, we shall call the quadratic form of FCTP as the non-linear FCTP.

The objective function (1) represents the minimization of the total transportation cost (i.e., the sum of total variable cost and total fixed-charge) associated with the transportation of different units of the item from all the origins to all the destinations using one or more trips of the vehicles. Eqs. (2) and (3) represent, respectively the supply and demand constraints of the item at the origins and destinations. Eq. (4) represents the capacity constraint of the vehicles, Eq. (5) shows that the FCTP is balanced, whereas, the non-negativity restrictions of the decision variables $x_{\lambda\mu\eta u}$ are given in (6).

A special case:

If in the proposed model of FCTP, we consider the restrictions of each region to be in zero level (i.e., the LSR value of each region is considered as zero), then the problem gets reduced to a FCTP in normal scenario given as follows.

$$\text{Minimize } Z = \underbrace{\sum_{\lambda=1}^{m}\sum_{\mu=1}^{n}\sum_{\eta=1}^{l}\sum_{u=1}^{N_\eta^\lambda} f\left(x_{\lambda\mu\eta u}\right)}_{\text{Total transportation cost}} \tag{7}$$

subject to the same constraints and non-negativity restrictions considered in the FCTP without any upper limit on transportation cost. In this case, the penalty for each pair of origin and destination becomes zero.

4. Solution methodology

In this paper, we solve the proposed model of FCTP in pandemic scenario presented in (7) using a GA based approach with suitable modifications. For this, a new crossover and a new mutation operator are designed and incorporated into the algorithm. In the following subsections, we discuss some components of GA such as generation of a chromosome, crossover and mutation, in details.

4.1. Generation of chromosome

Many researchers have used different encoding procedures to represent individual chromosomes, such as matrix representation [17,28,44], spanning tree [9–11,13] and priority-based encoding [14] to solve FCTP and its variants. Among these, the encoding procedures, namely, spanning tree and priority-based encoding are suitable for FCTPs, in which only one type of vehicle with no capacity constraint are available for each pair of an origin and a destination, and a vehicle can ship items to a destination in one trip at most. Thus, it is very difficult to incorporate these encoding procedures into our proposed FCTP. Moreover, these representations need encoding and decoding procedure to understand the transportation scheme corresponding to a solution. So, we use the matrix representation to represent an individual chromosome. As the decision variable $x_{\lambda\mu\eta u}$ has four indices, a four-dimensional matrix is used to represent a chromosome. The process of generation of a chromosome is given in Algorithm 1.

To constitute an initial population of size X_0, Algorithm 1 is repeatedly used. We now illustrate the process of generation of a chromosome for the proposed model of FCTP with two origins, three destinations and two vehicles using Algorithm 1.

Example 1. Let us consider a transportation network consisting of two origins O_1, O_2, two destinations D_1, D_2 and V_1, V_2 be two vehicles capable of carrying 10 and 20 units of the item, respectively, are available at each origin. Let the availability of the item at the origins O_1, O_2 be 30, 50 units and the demand for the items at the destinations be D_1, D_2 and 45, 35 units, respectively.

The process of generation of a chromosome for Example 1 is described below.

Iteration 1: Initially, Set $a_1 \leftarrow 30, a_2 \leftarrow 50, b_1 \leftarrow 45, b_2 \leftarrow 35$. Then $sum = 80$. Also, set $N_\eta^\lambda \leftarrow 0 (\lambda = 1, 2; \eta = 1, 2)$; $x_{\lambda\mu\eta u} \leftarrow 0 \forall \lambda, \mu, \eta, u$; $marko_\lambda \leftarrow 0 (\lambda = 1, 2)$ and $markd_\mu \leftarrow 0 (\mu = 1, 2)$ (*Step 1*). Let the origin O_1, the destination D_2 and the vehicle V_2 be selected (*Step 2*). Since $N_2^1 = 0$, the value of N_2^1 is changed to 1 (*Step 3*). Now, $Q = 20 (= minimum\{30, 35, 20 - 0\})$ and the updated values are $x_{1221} = 20, a_1 = 10, a_2 = 50, b_1 = 45, b_2 = 15, sum = 60$ and $N_2^1 = 2$ (*Step 4*). Since the value of $sum = 60 > 0$, we go to Step 2.

Iteration 2: Let the origin O_1, the destination D_2 and the vehicle V_1 be selected (*Step 2*). Since $N_1^1 = 0$, the value of N_1^1 is changed to 1 (*Step 3*). Now, $Q = 10 (= minimum\{10, 15, 10 - 0\})$ and the updated values are $x_{1211} = 10, a_1 = 0, a_2 = 50, b_1 = 45, b_2 = 5, sum = 50$ and $N_1^1 = 2$ (*Step 4*). Since a_1 becomes 0, the value of $marko_1$ is changed to 1 and the updated values are $marko_1 = 1, marko_2 = 0, markd_1 = 0, markd_2 = 0$. Since the value of $sum = 50 > 0$, we go to Step 2.

Algorithm 1 Generation of a chromosome

Step 1 : Set $sum \leftarrow \sum_{\lambda=1}^{m} a_\lambda$, $N_\eta^\lambda \leftarrow 0$ $(\lambda = 1, 2, \ldots, m;\ \eta = 1, 2, \ldots, l)$ and $x_{\lambda\mu\eta u} \leftarrow 0\ \forall \lambda, \mu, \eta, u$. Also, set $marko_\lambda \leftarrow 0$ $(\lambda = 1, 2, \ldots, m)$ and $markd_\mu \leftarrow 0$ $(\mu = 1, 2, \ldots, m)$.

Step 2 : Select an origin, say, $O_{\lambda'}$ such that $marko_{\lambda'} = 0$ and a destination $D_{\mu'}$ such that $markd_{\mu'} \leftarrow 0$, at random. Then select any vehicle, say, $V_{\eta'}$ $(\eta' \in \{1, 2, \ldots, l\})$. Go to Step 3.

Step 3 : Check if $N_{\eta'}^{\lambda'} = 0$? If yes, then change the value of $N_{\eta'}^{\lambda'}$ to 1.

Step 4 : Compute $Q \leftarrow minimum\left\{a_{\lambda'}, b_{\mu'}, e_{\eta'} - x_{\lambda'\mu'\eta' N_{\eta'}^{\lambda'}}\right\}$ and do the following:

$x_{\lambda'\mu'\eta' N_{\eta'}^{\lambda'}} \leftarrow x_{\lambda'\mu'\eta' N_{\eta'}^{\lambda'}} + Q;\ a_{\lambda'} \leftarrow a_{\lambda'} - Q;\ b_{\mu'} \leftarrow b_{\mu'} - Q; sum \leftarrow sum - Q.$

$If\, e_{\eta'} = x_{\lambda'\mu'\eta' N_{\eta'}^{\lambda'}}$, then $N_{\eta'}^{\lambda'} \leftarrow N_{\eta'}^{\lambda'} + 1$.

Step 5 : If $a_{\lambda'} = 0$, set $marko_{\lambda'} = 1$. If $b_{\mu'} = 0$, set $markd_{\mu'} = 1$.

Step 6 : Check if $sum > 0$? If yes, go to Step 2, otherwise, go to Step 7.

Step 7 : Print the chromosome $(x_{\lambda\mu\eta u})_{\lambda=1,\mu=1,\eta=1,u=1}^{m,n,l,N_\eta^\lambda}$.

Table 1
A chromosome generated for Example 1 using Algorithm 1.

Origin →	D_1				D_2			a_i
Destination ↓	V_1		V_2		V_1		V_2	
	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	
O_1	–	–	–	–	10	–	20	30
O_2	10	–	20	15	5	–	–	50
b_j	45				35			

Iteration 3: Let the origin O_2, the destination D_1 and the vehicle V_1 be selected (*Step 2*). Since $N_1^2 = 0$, the value of N_1^2 is changed to 1 (*Step 3*). Now, $Q = 10 (= minimum\,\{50, 45, 10-0\})$ and the updated values are $x_{2111} = 10, a_1 = 0, a_2 = 40, b_1 = 35, b_2 = 5, sum = 40$ and $N_1^2 = 2$ (*Step 4*). Since the value of $sum = 40 > 0$, we again go to Step 2.

Iteration 4: Let the origin O_2, the destination D_2 and the vehicle V_1 be selected (*Step 2*). Now, $N_1^2 = 2$. Thus, $Q = 5 (= minimum\,\{40, 5, 10-0\})$ and the updated values become $x_{2212} = 5, a_1 = 0, a_2 = 35, b_1 = 35, b_2 = 0$ and $sum = 35$ (*Step 4*). Since b_1 becomes 0, the value of $markd_1$ is changed to 1 and the updated values are $marko_1 = 1, marko_2 = 0, markd_1 = 1, markd_2 = 0$. Since the value of $sum = 53 > 0$, we go to Step 2.

Iteration 5: Let the origin O_2, the destination D_1 and the vehicle V_2 be selected (*Step 2*). Since $N_2^2 = 0$, the value of N_2^2 is changed to 1 (*Step 3*). Now, $Q = 20 (= minimum\,\{35, 35, 20-0\})$ and the updated values become $x_{2121} = 20, a_1 = 0, a_2 = 15, b_1 = 15, b_2 = 0$, $sum = 15$ and $N_2^2 = 2$ (*Step 4*). Since the value of $sum = 15 > 0$, we go to Step 2.

Iteration 6: Let the origin O_2, the destination D_1 and the vehicle V_2 be selected (*Step 2*). Now, $N_2^2 = 2$. Thus, $Q = 15 (= minimum\,\{15, 15, 20-0\})$ and the updated values are $x_{2122} = 15, a_1 = 0, a_2 = 0, b_1 = 0, b_2 = 0$ and $sum = 0$ (*Step 4*). Since the value of $sum = 0$, the process of generation of chromosome is completed.

The generated chromosome is given in Table 1 and the transportation scheme is represented diagrammatically in Fig. 1.

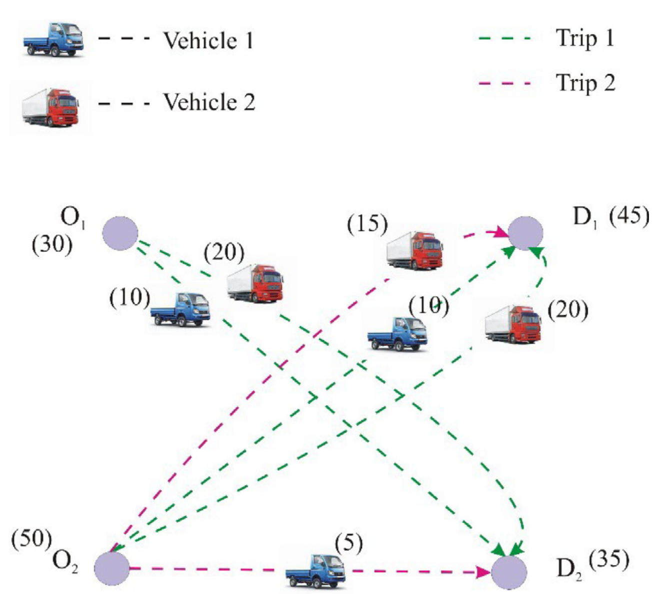

Fig. 1. Transportation scheme corresponding to the chromosome given in Table 1.

After the initial population is constituted, the fitness value of each chromosome is evaluated. In this paper, the binary tournament selection is used.

Algorithm 2 Proposed crossover process

Input: Parent chromosomes $ch_1(x_{\lambda\mu\eta u})$ and $ch_2(y_{\lambda\mu\eta u})$

Output: A child chromosome $ch(z_{\lambda\mu\eta u})$

Step 1 : Let $a'_\lambda(\lambda = 1,2,\ldots,m)$ and b'_μ ($\mu = 1,2,\ldots,n$) be the set of variables that are assigned values $a'_\lambda \leftarrow a_\lambda, \lambda = 1,2,\ldots,m$ and $b'_\mu \leftarrow b_\mu, \mu = 1,2,\ldots,n$. Also, assign $N^\lambda_\eta(z) \leftarrow 0$ ($\lambda = 1,2,\ldots,m; \eta = 1,2,\ldots,l$), $z_{\lambda\mu\eta u} \leftarrow 0\ \forall\lambda,\mu,\eta,u$ and $sum \leftarrow \sum_{\lambda=1}^m a'_\lambda$.

Step 2 : Obtain the set of origin-destination pairs from the parent chromosomes $ch_1(x_{\lambda\mu\eta u})$ and $ch_2(y_{\lambda\mu\eta u})$, so that there is transportation of a positive amount of the items from that origin to that destination using at least one of the available vehicles in at least one trip and list the distinct origin-destination pairs in $LIST[]$. Let the number of such edges be $count$.

Step 3 : Let $sign_\lambda = 0$ ($\lambda = 1,2,\ldots,count$) be a set of variables that are assigned values $sign_\lambda = 0, \lambda = 1,2,\ldots,count$. Go to ***Step 4***.

Step 4 : Select $id \in \{1,2,\ldots,count\}$ at random such that $sign_{id} = 0$. Let the edge $LIST[id]$ connects origin O_α and destination D_β. Select V_ξ ($\xi \in \{1,2,\ldots,l\}$) at random.

Step 5 : If $N^\alpha_\xi(z) = 0$, then $N^\alpha_\xi(z) \leftarrow N^\alpha_\xi(z) + 1$.

Step 6 : Assign $u = N^\alpha_\xi(z)$ and compute $Q = minimum\{a'_\alpha, b'_\beta, e_\xi - z_{\alpha\beta\xi u}\}$. Update the values of the following variables:

$z_{\alpha\beta\xi u} \leftarrow z_{\alpha\beta\xi u} + Q, a'_\alpha \leftarrow a'_\alpha - Q,\ b'_\beta \leftarrow b'_\beta - Q, sum \leftarrow sum - Q, N^\alpha_\xi(z) \leftarrow N^\alpha_\xi(z) + 1.$

Step 7 : If $a'_\alpha = 0$, then for any $id' \in \{1,2,\ldots,count\}$, if the edge $LIST[id']$ is connected to the origin O_α, assign $sign_{id'} = 1$. If $b'_\beta = 0$, then for any $id' \in \{1,2,\ldots,count\}$, if the edge $LIST[id']$ is connected to the destination D_β, assign $sign_{id'} = 1$.

Step 8 : If $sum > 0$, go to ***Step 4***, otherwise go to ***Step 9***.

Step 9 : Print the chromosome $ch(z_{\lambda\mu\eta u})$.

4.2. Crossover

In this paper, we develop a new crossover for the proposed model of FCTP. In this crossover, two child chromosome are obtained from two parent chromosomes, the selection of parent chromosomes being random from the mating pool. The process of generation of a child chromosome say, $ch \leftarrow (z_{\lambda\mu\eta u})$ from two parent chromosomes $ch_1 \leftarrow (x_{\lambda\mu\eta u})$ and $ch_2 \leftarrow (y_{\lambda\mu\eta u})$ using the proposed crossover is provided in Algorithm 2.

After both the child chromosomes are obtained, the best two chromosomes among the parent and child chromosomes are selected to constitute the population of next generation.

Let us now illustrate the procedure of the proposed crossover two particular chromosomes $P_1(x_{\lambda\mu\eta u})$ and $P_2(y_{\lambda\mu\eta u})$ of the transportation network considered in Example 1. The chromosomes P_1 and P_2 are given in Table 2, the transportation network for which are represented diagrammatically in Fig. 2. Here, we illustrate the process of generation of a child chromosome $Q_1(z_{\lambda\mu\eta u})$ only, the process of generation of the other child $Q_2(z'_{\lambda\mu\eta u})$ being similar.

Generation of a child chromosome from the parent chromosomes P_1 and P_2:

At first, assign $a'_1 \leftarrow 30$, $a'_2 \leftarrow 50$, $b'_1 \leftarrow 45$, $b'_2 \leftarrow 35$, $N^\lambda_\eta(z) \leftarrow 0(\lambda = 1,2; \eta = 1,2)$, $sum \leftarrow 80(= \sum_{\lambda=1}^m a'_\lambda)$ and $z_{\lambda\mu\eta u} \leftarrow 0\forall\lambda,\mu,\eta,u$(***Step 1***). We have, $count = 4$ and $LIST[4] = \{(O_1,D_1),(O_1,D_2),(O_2,D_1) \text{ and } (O_2,D_2)\}$ (***Step 2***). Assign $sign_\lambda = 0(\lambda = 1,2,3,4)$ (***Step 3***).

Let us choose $id = 1$. Thus, $\alpha = 1$ and $\beta = 1$. Also select $\xi = 2$ (***Step 4***). Since $N^1_2(z) = 0$, we change the value of $N^1_2(z)$ to 1 (***Step 5***). Then $u = 1$ and $Q \leftarrow 20(minimum\{30,45,20\})$, i.e., an amount of 20 units of the items is transported from the origin O_1 to the destination D_1 in first trip of vehicle V_2 originating from O_1. Then z_{1121}=20, $a'_1 = 10$, $a'_2 = 50$, $b'_1 = 25$, $b'_2 \leftarrow 35$, $sum = 60$ and $N^1_2(z) = 2$(***Step 6***). Since $sum = 60 > 0$, we go to ***Step 4***.

Since $sign_\lambda = 0\forall\lambda = 1,2,3,4$, we can choose $id \in \{1,2,3,4\}$. Let us choose $id = 4$. Thus, $\alpha = 2$ and $\beta = 2$. Also select $\xi = 2$ (***Step 4***). Since $N^2_2(z) = 0$, we change the value of $N^2_2(z)$ to 1 (***Step 5***). Then $u = 1$ and $Q \leftarrow 20(minimum\{50,35,20\})$, i.e., an amount of 20 units of the items is transported from the origin O_2 to the destination D_2 in first trip of vehicle V_2 originating from O_2. Then z_{2221}=20, $a'_1 = 10$, $a'_2 = 30$, $b'_1 = 25$, $b'_2 \leftarrow 15$, $sum = 40$ and $N^2_2(z) = 2$(***Step 6***). Since $sum = 40 > 0$, we go to ***Step 4***.

Since $sign_\lambda = 0\forall\lambda = 1,2,3,4$, we can choose $id \in \{1,2,3,4\}$. Let us choose $id = 2$. Thus, $\alpha = 1$ and $\beta = 2$. Also select $\xi = 1$ (***Step 4***). Since $N^1_1(z) = 0$, we change the value of $N^1_1(z)$ to 1 (***Step 5***). Then $u = 1$ and $Q \leftarrow 10(minimum\{10,15,10\})$, i.e., an amount of 10 units of the items is transported from the origin O_1 to the destination D_2 in first trip of vehicle V_1 originating from O_1. Then z_{1211}=10, $a'_1 = 0$, $a'_2 = 30$, $b'_1 = 25$, $b'_2 \leftarrow 5$, $sum = 30$ and $N^2_2(z) = 2$(***Step 6***). Since a'_1 becomes 0, $sign_1 = 1$ and $sign_2 = 1$ (***Step 7***). Again, $sum = 30 > 0$, we go to ***Step 4***.

Since $sign_1 = 1$, $sign_2 = 1$, $sign_3 = 0$ and $sign_4 = 0$, we can choose $id \in \{3,4\}$. Let us choose $id = 4$. Thus, $\alpha = 2$ and $\beta = 2$. Also select $\xi = 1$ (***Step 4***). Since $N^2_1(z) = 0$, we change the value of $N^2_1(z)$ to 1 (***Step 5***).

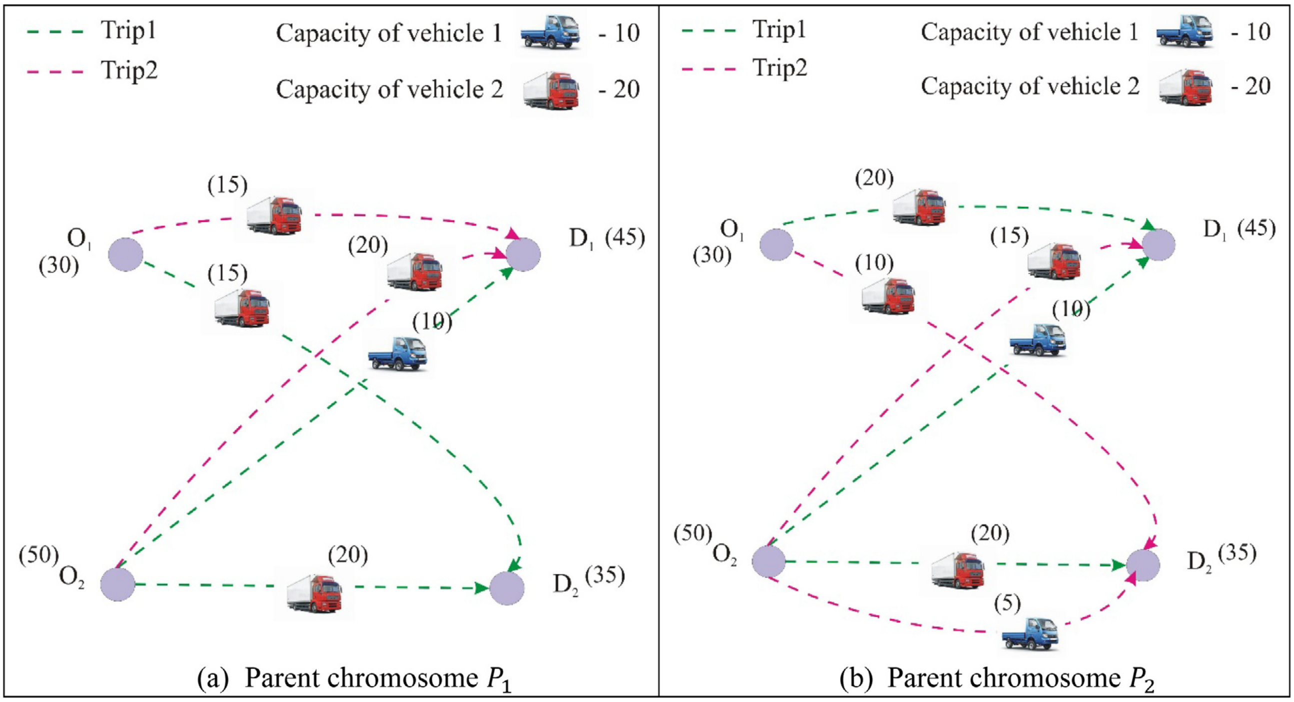

Fig. 2. Diagrammatic representation of parent chromosomes P_1 and P_2 chosen for performing crossover.

Table 2
Matrix representation of the parent chromosomes P_1 and P_2.

Origin →	*Parent* P_1								*Parent* P_2							
	D_1				D_2				D_1				D_2			
Destination ↓	V_1		V_2		V_1		V_2		V_1		V_2		V_1		V_2	
	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Tipr*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2
O_1	–	–	–	15	–	–	15	–	–	–	20	–	–	–	–	10
O_2	10	–	–	20	–	–	20	–	10	–	–	15	–	5	20	–

Then $u = 1$ and $Q \leftarrow 5(minimum\{30, 5, 10\})$, i.e., an amount of 5 units of the item is transported from the origin O_2 to the destination D_2 in first trip of vehicle V_1 originating from O_2. Then, z_{2211}=5, $a'_1 = 0$, $a'_2 = 25$, $b'_1 = 25$, $b'_2 = 0$, $sum = 25$ and $N_1^2(z) = 2$(***Step 6***). Since b'_2 becomes 0, $sign_1 = 1$, $sign_2 = 1$, $sign_3 = 0$ and $sign_4 = 1$ (***Step 7***). Again, since $sum = 25 > 0$, we go to ***Step 4***.

Since $sign_1 = 1$, $sign_2 = 1$, $sign_3 = 0$ and $sign_4 = 1$, the only value that can be chosen is $id = 3$. Thus, $\alpha = 2$ and $\beta = 1$. Also, select $\xi = 1$ (***Step 4***). We have $N_1^2(z) = 2$. Thus, $u = 2$ and $Q \leftarrow 10(minimum\{25, 25, 10\})$, i.e., an amount of 10 units of the items is transported from the origin O_2 to the destination D_1 in second trip of vehicle V_1 originating from O_2. Then z_{2112}=10, $a'_1 = 0$, $a'_2 = 15$, $b'_1 = 15$, $b'_2 = 0$, $sum = 15$ and $N_1^2(z) = 3$(***Step 6***). Since $sum = 15 > 0$, we go to ***Step 4***.

Since $sign_1 = 1$, $sign_2 = 1$, $sign_3 = 0$ and $sign_4 = 1$, the only value that can be chosen is $id = 3$. Thus, $\alpha = 2$ and $\beta = 1$. Let us choose $\xi = 2$ (***Step 4***). We have $N_2^2(z) = 2$. Thus, $u = 2$ and $Q \leftarrow 15(minimum\{15, 15, 20\})$, i.e., an amount of 15 units of the items is transported from the origin O_2 to the destination D_1 in the second trip of vehicle V_2 originating from O_2. Then z_{2122}=15, $a'_1 = 0$, $a'_2 = 0$, $b'_1 = 0$, $b'_2 = 0$, $sum = 0$ and $N_1^2(z) = 3$(***Step 6***). Since $sum = 0$, the generation of the child chromosome $Q_1(z_{\lambda\mu\eta u})$ is completed.

The child chromosomes Q_1 and Q_2 obtained from the parent chromosomes P_1 and P_2 are given in Table 3. The diagrammatic representation of Q_1 and Q_2 are given in Fig. 3.

4.3. Mutation

In this paper, a new mutation suitable for the proposed problem is developed. The process of the proposed mutation operation is described in Algorithm 3.

Let us illustrate the process of the proposed mutation for a particular chromosome $ch \leftarrow (x_{\lambda\mu\eta u})$, as given in Table 4, for which the transportation scheme is represented diagrammatically in Fig. 4(a). Let the chromosome to be obtained after the mutation be $ch' \leftarrow (x'_{\lambda\mu\eta u})$.

Assign $N_\eta^\lambda(x') \leftarrow N_\eta^\lambda(x)(\lambda = 1, 2; \eta = 1, 2)$ and $x'_{\lambda\mu\eta u} \leftarrow x_{\lambda\mu\eta u} \forall \lambda, \mu, \eta, u$ (***Step 1***). Let us select $\beta_1 = 1$ and $\alpha_1 = 1$, $\xi_1 = 2$. We get $u_1 = 2$ (***Step 2***). Again, let us select $\beta_2 = 2$ and $\alpha_2 = 2$, $\xi_2 = 2$ and $u_2 = 2$ (***Step 3-5***). Then $Q = 10(minimum\{x'_{1122} = 10, x'_{2222} = 15\})$ and the updated values are obtained as $x'_{1122} = 0$, $x'_{2222} = 5$. Also, since $u_1 = N_2^1(x')$ and $x'_{1122} = 0$, the value of $N_2^1(x')$ is decreased by 1 i.e., $N_2^1\left(x'\right) = 1$ (***Step 6***). Next, we have $Q_1 = 10$ and select the vehicle say, V_1(***Step 7***). Since $N_1^1\left(x'\right) = 0$, the value of $N_1^1\left(x'\right)$ is increased by 1 i.e., $N_1^1\left(x'\right) = 1$ (***Step 8***). Then $q_1 = 10(minimum\{10, 10 - 0\})$ and $x'_{1211} = 10, Q_1 = 0$ (***Step 9***). Since $Q_1 = 0$, we go to ***Step 11*** (***Step 10***).

We have $Q_2 = 10$ and select the vehicle say, V_1(***Step 11***). Now, $N_1^2\left(x'\right) = 2$ and we obtain $q_2 = 5(minimum\{10, 10 - 5\})$ and hence $x'_{2112} = 10$, $Q_2 = 5$. Also, since $e_1 = x_{1212}$, the value of $N_1^2\left(x'\right)$ is increased by 1 i.e., $N_1^2\left(x'\right) = 3$(***Step 13***). Since $Q_2 = 5 > 0$, we again go to ***Step 11*** and select a vehicle say, V_1. Now, $N_1^2\left(x'\right) = 3$ and we obtain $q_2 = 5(minimum\{5, 10 - 0\})$ and

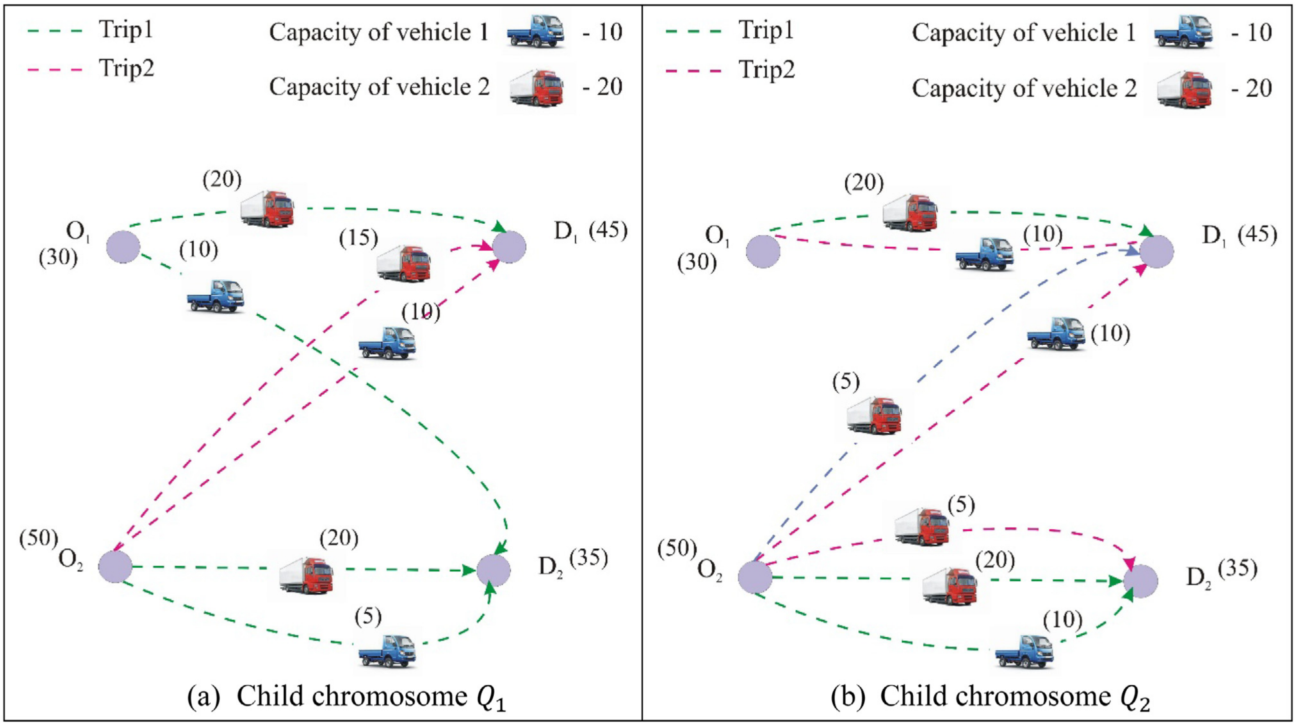

Fig. 3. Child chromosomes Q_1 and Q_2 obtained by applying the proposed crossover.

Table 3
Matrix representation of the children Q_1 and Q_2.

Origin →	*Child*Q_1								*Child*Q_2								
	D_1				D_2				D_1					D_2			
Destination ↓	V_1		V_2		V_1		V_2		V_1		V_2			V_1		V_2	
	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*3	*Trip*1	*Trip*2	*Trip*1	*Trip*2
O_1	–	–	20	–	10	–	–	–	–	10	20	–	–	–	–	–	–
O_2	–	10	–	15	5	–	20	–	–	10	–	–	5	10	–	20	5

Table 4
Matrix representation of the chromosomes before and after mutation.

Origin →	Chromosome before mutation							Chromosome after mutation						
	D_1				D_2			D_1				D_2		
Destination ↓	V_1		V_2		V_1	V_2		V_1			V_2	V_1	V_2	
	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*1	*Trip*1	*Trip*2	*Trip*1	*Trip*2	*Trip*3	*Trip*1	*Trip*1	*Trip*1	*Trip*2
O_1	–	–	20	10	–	–	–				20	10		
O_2	10	5	–	–	–	20	15	10	10	5			20	5

hence $x'_{2113} = 5$, $Q_2 = 0$ (***Step 13***). Since $Q_2 = 0$, the process is completed and is given in Table 4. A diagrammatic representation of the chromosome after mutation is given in Fig. 4(b).

5. Experimental results

For experimental purpose, we consider five numerical examples of the proposed model of FCTP of different size, which are then solved using the algorithm. In this section, we first discuss the dataset generation and the parameter settings used. Then, the numerical examples are solved using the algorithm and the results are analyzed. Finally, the performance comparison with existing methods are presented. The configuration of the system in which the program is executed: Intel® x-64 based processor CPU N3700 @ 1.60 GHz with 4.0 GB RAM.

5.1. Dataset

The proposed model is different from the existing models of FCTP, and so, we generate new datasets according to our model. For experimental purpose, we consider five numerical examples of the same size given in Lofti & Tavakkoli-Moghaddam [14] (i.e., $4 \times 5, 5 \times 10, 10 \times 10, 10 \times 20$ and 20×30). Thus, for these numerical examples, we take the availability and demands for the item as given in Lofti & Tavakkoli-Moghaddam [14]. We consider two vehicles, say, V_1 and V_2 with capacities 10 and 20 units, respectively, corresponding to each numerical example. The variable and fixed costs corresponding to the vehicles V_1 and V_2 for the numerical example with 20 origins and 30 destinations are generated randomly within the ranges [4, 12] and [50, 135], and are presented in Appendix. The variable and fixed cost matrices for a numerical example of smaller size, say, $m' \times n'$ (where

Algorithm 3 Proposed mutation process

Input: Chromosome $ch \leftarrow (x_{\lambda\mu\eta u})$ before mutation

Output: Chromosome after mutation $ch' \leftarrow (x'_{\lambda\mu\eta u})$.

Step 1 : Initially, assign $N_\eta^\lambda(x') \leftarrow N_\eta^\lambda(x)$ $(\lambda = 1,2,\dots,m; \eta = 1,2,\dots,l)$ and $x'_{\lambda\mu\eta u} \leftarrow x_{\lambda\mu\eta u}$ $\forall\ \lambda,\mu,\eta,u$.

Step 2 : Select a $\beta_1 \in \{1,2,\dots,n\}$ at random. Then choose $\alpha_1 \in \{1,2,\dots,m\}$ and $\xi_1 \in \{1,2,\dots,l\}$ at random such that $x'_{\alpha_1\beta_1\xi_1 u} > 0$ for at least one $u \in \{1,2,\dots,N_{\xi_1}^{\alpha_1}(x')\}$.Obtain $u_1 = max\{u: u \in \{1,2,\dots,N_{\xi_1}^{\alpha_1}(x')\}$ and $x'_{\alpha_1\beta_1\xi_1 u} > 0\}$.

Step 3 : Select $\beta_2 \in \{1,2,\dots,n\}$ at random such that $\beta_2 \neq \beta_1$.

Step 4 : Check If $\exists\ \alpha_2 \in \{1,2,\dots,m\}$ such that $\alpha_2 \neq \alpha_1$ and $x'_{\alpha_2\beta_2\xi_2 u} > 0$ for some $\xi_2 \in \{1,2,\dots,l\}$ and $u \in \{1,2,\dots,N_{\xi_2}^{\alpha_2}(x')\}$ .If yes, go to next step, otherwise go to ***Step 3***.

Step 5 : Obtain $u_2 = max\{u: u \in \left\{1,2,\dots,N_{\xi_2}^{\alpha_2}(x')\right\}: x'_{\alpha_2\beta_2\xi_2 u} > 0\}$.

Step 6 : Obtain $Q \leftarrow minimum\{x'_{\alpha_1\beta_1\xi_1 u_1}, x'_{\alpha_2\beta_2\xi_2 u_2}\}$. Then do the following:

$x'_{\alpha_1\beta_1\xi_1 u_1} \leftarrow x'_{\alpha_1\beta_1\xi_1 u_1} - Q$;

If $x'_{\alpha_1\beta_1\xi_1 u_1} = 0$ and $u_1 = N_{\xi_1}^{\alpha_1}(x')$, then assign $N_{\xi_1}^{\alpha_1}(x') \leftarrow N_{\xi_1}^{\alpha_1}(x') - 1$.

If $x'_{\alpha_1\beta_1\xi_1 u_1} = 0$ and $u_1 \neq N_{\xi_1}^{\alpha_1}(x')$, then do the following:

For $u = u_1 + 1,\dots,N_{\xi_1}^{\alpha_1}(x')$,

$x'_{\alpha_1\beta_1\xi_1 u-1} \leftarrow x'_{\alpha_1\beta_1\xi_1 u}$;

End for

End if

$x'_{\alpha_2\beta_2\xi_2 u_2} \leftarrow x'_{\alpha_2\beta_2\xi_2 u_2} - Q$;

If $u_2 = N_{\xi_2}^{\alpha_2}(x')$ and $x'_{\alpha_2\beta_2\xi_2 u_2} = 0$, then assign $N_{\xi_2}^{\alpha_2}(x') \leftarrow N_{\xi_2}^{\alpha_2}(x') - 1$.

If $x'_{\alpha_2\beta_2\xi_2 u_2} = 0$ and $u_2 \neq N_{\xi_2}^{\alpha_2}(x')$, then do the following:

For $u = u_1 + 1,\dots,N_{\xi_2}^{\alpha_2}(x')$,

$x'_{\alpha_2\beta_2\xi_2 u-1} \leftarrow x'_{\alpha_2\beta_2\xi_2 u}$;

End for

End if

Step 7 : Assign $Q_1 \leftarrow Q$.

Step 8 : Select any vehicle, say, $V_{\xi_3}(\xi_3 \in \{1,2,\dots,l\})$. Check if $N_{\xi_3}^{\alpha_1}(x') = 0$? If yes, then change the value of $N_{\xi_3}^{\alpha_1}(x')$ to 1.

Step 9 : Compute $q_1 \leftarrow minimum\left\{Q_1, e_{\xi_3} - x_{\alpha_1\beta_2\xi_3 N_{\xi_3}^{\alpha_1}}\right\}$ and do the following:

$x_{\alpha_1\beta_2\xi_3 N_{\xi_3}^{\alpha_1}} \leftarrow x_{\alpha_1\beta_2\xi_3 N_{\xi_3}^{\alpha_1}} + q_1$;

$Q_1 \leftarrow Q_1 - q_1$;

If $e_{\xi_3} = x_{\alpha_1\beta_2\xi_3 N_{\xi_3}^{\alpha_1}}$, then $N_{\xi_3}^{\alpha_1} \leftarrow N_{\xi_3}^{\alpha_1} + 1$.

Step 10 : Check if $Q_1 > 0$? If yes, go to ***Step 9***, else go to next step.

Step 11 : Assign $Q_2 \leftarrow Q$.

Step 12 : Select any vehicle, say, $V_{\xi_4}(\xi_4 \in \{1,2,\dots,l\})$. Check if $N_{\xi_4}^{\alpha_2}(x') = 0$? If yes, then change the value of $N_{\xi_4}^{\alpha_2}(x')$ to 1.

Step 13 : Compute $q_2 \leftarrow minimum\left\{Q_2, e_{\xi_4} - x_{\alpha_2\beta_1\xi_4 N_{\xi_4}^{\alpha_2}}\right\}$ and do the following:

$x_{\alpha_2\beta_1\xi_4 N_{\xi_4}^{\alpha_2}} \leftarrow x_{\alpha_2\beta_1\xi_4 N_{\xi_4}^{\alpha_2}} + q_2$;

$Q_2 \leftarrow Q_2 - q_2$;

If $e_{\xi_4} = x_{\alpha_2\beta_1\xi_4 N_{\xi_4}^{\alpha_2}}$, then $N_{\xi_4}^{\alpha_2} \leftarrow N_{\xi_4}^{\alpha_2} + 1$.

Step 14 : Check if $Q_2 > 0$? If yes, go to ***Step 12***, else go to next step.

Step 15 : Print the chromosome $ch' \leftarrow (x'_{\lambda\mu\eta u})$.

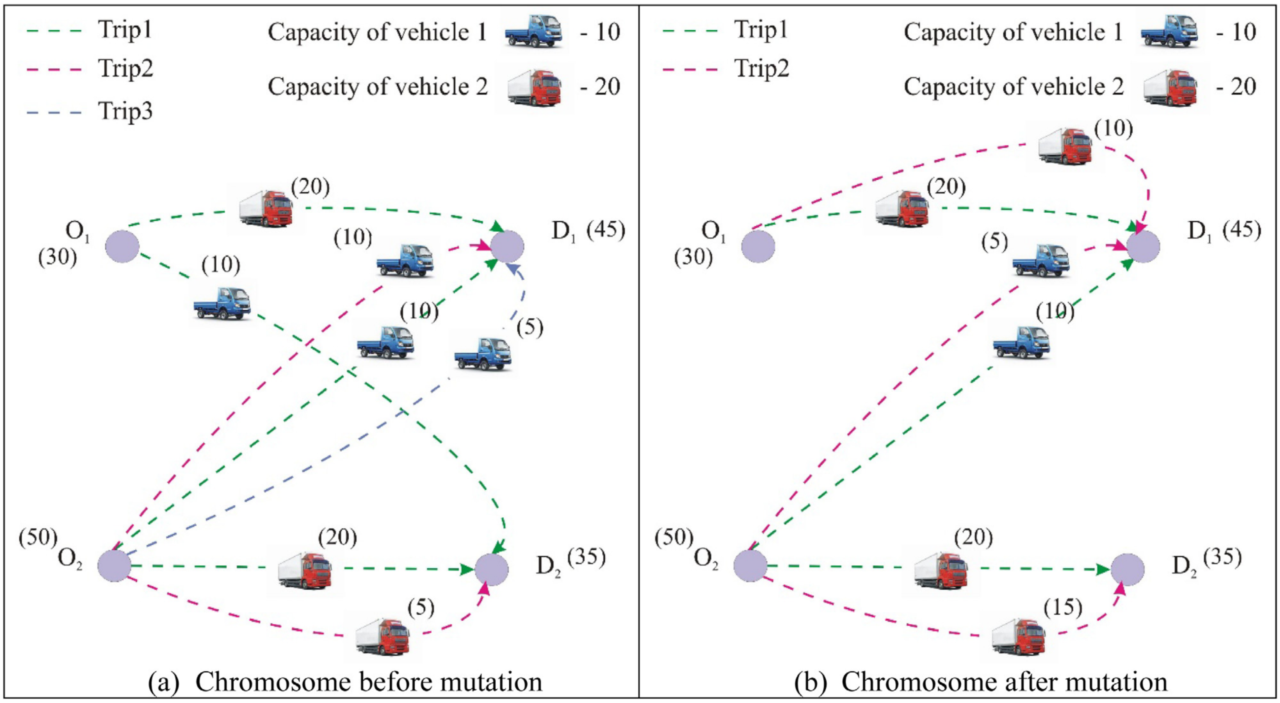

Fig. 4. Chromosomes before and after mutation.

Table 5
Categorization of origins and destinations for the numerical examples.

# Example	Category of origins	Category of destinations
1	*Green*: 1; *Orange*: 2, 4; *Red*: 3	*Green*: 3, 5; *Orange*: 1,2; *Red*: 4
2	*Green*: 1, 5; *Orange*: 2, 4; *Red*: 3	*Green*: 3, 5, 10; *Orange*: 1, 2, 8, 9;*Red*: 4, 6, 7
3	*Green*: 1, 5, 9; *Orange*: 2, 4, 7, 8; *Red*: 3, 6, 10	*Green*: 3, 5, 10; *Orange*: 1,2, 8, 9;*Red*: 4, 6, 7
4	*Green*: 1, 5, 9; *Orange*: 2, 4, 7, 8; *Red*: 3, 6, 10	*Green*: 3, 5, 10, 14, 17; *Orange*: 1, 2, 8, 9, 12, 15, 16,19; *Red*: 4, 6, 7, 11, 13, 18, 20
5	*Green*: 1, 5, 9, 14, 17; *Orange*: 2, 4, 7, 8, 12, 15, 16, 19; *Red*: 3, 6, 10, 11, 13, 18, 20	*Green*: 3, 5, 10, 14, 17, 23, 28; *Orange*: 1,2, 8, 9, 12, 15, 16,19, 21, 22, 26, 29, 30; *Red*: 4, 6, 7, 11, 13, 18, 20, 24, 25, 27.

$m' \leq 20, n' \leq 30$) is taken as the sub-matrix of order $m' \times n'$, starting from the north-west corner of the corresponding matrix of size 20×30. For each numerical example, we categorize the regions in three groups, in which the level of restrictions are 'high', 'medium' and 'low', and are marked in 'Red', 'Orange' and 'Green', respectively. The list of origins and destinations belonging to each group are presented in Table 5.

5.2. Parameter settings

To obtain the best possible solution using the algorithm, the control parameters of the algorithm such as X_0, It_{max}, p_{cros} and p_{mut} are set to values that produce promising results in preliminary testing. The parameter values of X_0, It_{max} used to solve the numerical examples of different size are shown in Table 6. The values of the parameters p_{cros} and p_{mut} are taken as 0.8 and 0.15 for each numerical example.

5.3. Results and discussion

In this section, we describe the method for computation of penalty for the proposed FCTP, which depends upon the level of restriction of the regions in which the origins and the destinations are located. The purpose of imposing penalty in the objective function is to lower the number of trips of vehicles if the level of restriction in the regions are 'high'. For this purpose, we associated a numerical value corresponding to each category of regions, and term as Level of Severity of Restriction (LSR) value. The process of computation of penalty is given as follows.

In a pandemic scenario, if the regions be categorized in K different groups, say, $G_1, G_2, \ldots, G_K$, then the region G_λ is assigned a LSR value υ_λ that lies between 1 and K in the relative ranking of the regions when arranged in increasing order of level of restrictions. The LSR value of a region is assigned zero, when no restrictions are imposed in a region. For a trip of any vehicle from an origin O_λ to a destination D_μ located in regions G_r and G_s respectively, the penalty is denoted by P_{rs}, and computed as $[\max\{\upsilon_r, \upsilon_s\} + |\upsilon_r - \upsilon_s|] * M$, where M is a large positive number and υ_r, υ_s are the LSR values of the regions G_r and G_s respectively. For solving the numerical examples, we have chosen the value of M as 100.0.

Explanation:

The reason of including the terms $\max\{\upsilon_r, \upsilon_s\}$ and $|\upsilon_r - \upsilon_s|$ in the penalty function is to consider higher penalty when either of the situation occurs, (i) at least one of the regions in which an origin or a destination situated takes large LSR value, i.e., the restriction is high (ii) the difference in LSR values of the two

Table 6
Parameters used to solve the numerical examples.

Cost function →	Classical		Linear fixed- charge		Non-linear fixed- charge	
# Numerical example	X_0	It_{max}	X_0	It_{max}	X_0	It_{max}
1	100	100	100	100	100	150
2	100	100	100	100	150	200
3	100	150	150	200	200	250
4	200	200	200	250	200	300
5	300	400	300	400	300	400

Table 7
Computation of penalty in a trip for all possible categories of regions.

Category of region in which origin is situated	LSR value of origin (v_r)	Category of region in which destination is situated	LSR value of destination (v_s)	Penalty value ($[\max\{v_r, v_s\} + \lvert v_r - v_s\rvert] * M$)
Green	0	Green	0	0
Green	0	Orange	1	$2M$
Green	0	Red	2	$4M$
Orange	1	Green	0	$2M$
Orange	1	Orange	1	M
Orange	1	Red	2	$3M$
Red	2	Green	0	$4M$
Red	2	Orange	1	$3M$
Red	2	Red	2	$2M$

Table 8
Information summary of results for the numerical examples of the proposed FCTP with the linear fixed-charge form of cost function.

Scenario →	Normal			Pandemic										
	Without consideration of upper limit on transportation cost as constraint			Without consideration of upper limit on transportation cost as constraint					With consideration of upper limit on transportation cost as constraint					
# Numerical example (Size)	Best found objective function value (A)	Penalty (B)	Total no. of trips (B)	Best found objective function value	Penalty	% Increase in objective function value with respect to (A)	Total no. of trips	% Decrease in penalty with respect to (B)	Upper limit on total transportation cost	Best found objective function value	Penalty	% Increase in objective function value with respect to (A)	Total no. of trips	% Decrease in penalty with respect to (B)
1 (4 × 5)	1619	$16M$	12	1779	$11M$	9.88	10	31.25	1750	1711	$14M$	5.68	11	12.5
2 (5 × 10)	2324	$24M$	15	3041	$18M$	30.85	17	25.0	2600	2591	$24M$	11.49	17	0.0
3 (10 × 10)	2713	$27M$	20	3504	$20M$	29.16	18	25.93	2850	2815	$25M$	3.76	19	7.41
4 (10 × 20)	4248	$48M$	29	5539	$33M$	30.39	30	31.25	5000	4980	$39M$	17.23	28	18.75
5 (20 × 30)	7069	$70M$	47	9341	$62M$	32.14	51	11.43	8500	8403	$64M$	18.87	50	8.57

regions associated with a tour of any vehicle is large, i.e., the level of restriction in one of the two regions is low, whereas, the level restriction in the other region is high.

Let us illustrate the process of computation of penalty for a particular example. For this, let us consider the transportation network given in Example 1 (Ref. Section 4.1.). Let us consider that the regions be categorized in three groups, and are marked in 'Red', 'Orange' and 'Green'. Then, the penalty for a single trip of a vehicle for different possible combinations of LSR values corresponding to an origin and a destination is given in Table 7.

In this section, we discuss the results obtained for the five numerical examples solved for each of the problems, namely, the proposed FCTP (given in (7)), the corresponding problem without any constraint on transportation cost and the problem in normal scenario (given in (8)). Each of the problems are solved taking three different forms of the cost function, viz., the linear fixed-charge form, quadratic fixed-charge form (non-linear) and the reduced classical form (a special case of the fixed charge forms in which the fixed costs are taken to be zero). Consequently, a total of 15 instances are solved for each problem, and a total of 45 (= 15 × 3) instances are solved in this paper. The best found objective function value, penalty value and the total number of trips for each example corresponding to the linear and quadratic form of cost function are presented in Table 8 and Table 9, respectively. The corresponding results for the reduced CTP are presented in Table 10. Due to the randomness nature of GA, 20 independent runs are taken for each instance of a numerical example.

The result shows that the transportation cost for each numerical example of the problem in pandemic scenario without

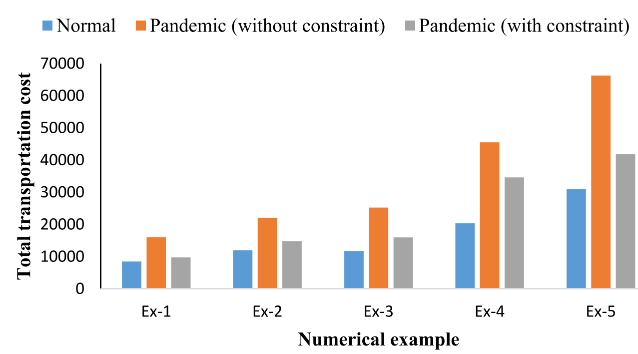

Fig. 5. Variation of total transportation cost corresponding the three problems for each numerical example.

the constraint is more in comparison to normal scenario, and for certain examples, the difference in transportation cost is significantly high. However, the set upper limit on transportation cost is effective in reducing the transportation cost. The percentage increase in transportation cost for the two problems (with and without constraint) in pandemic scenario with respect to the problem in normal scenario are computed for each form of the cost function and given in Tables 8–10.

Since the penalty value is a measure of the number of trips between regions with different levels of restrictions (i.e., LSR values), we have computed the expected penalty for each example of the problem in normal scenario given in Eq. (8) considering the same categorization of regions, and presented in respective

Table 9
Information summary of results for the numerical examples of the proposed FCTP with the quadratic fixed-charge form of cost function.

Scenario →	Normal			Pandemic										
	Without consideration of upper limit on transportation cost as constraint			Without consideration of upper limit on transportation cost as constraint					With consideration of upper limit on transportation cost as constraint					
# Numerical example (Size)	Best found objective function value (A)	Penalty (B)	Total no. of trips (C)	Best found objective function value	Penalty	% Increase in objective function value with respect to (A)	Total no. of trips	% Decrease in penalty with respect to (B)	Upper limit on total transportation cost	Best found objective function value	Penalty	% Increase in objective function value with respect to (A)	Total no. of trips	% Decrease in penalty with respect to (B)
1 (4 × 5)	8489	30*M*	23	16060	11*M*	89.19	11	63.33	10000	9765	17*M*	15.03	14	43.33
2 (5 × 10)	11996	54*M*	38	22082	18*M*	84.08	18	66.67	15500	14835	27*M*	23.67	22	50.0
3 (10 × 10)	11765	56*M*	36	25250	19*M*	112.41	20	66.07	16000	15996	26*M*	35.96	21	53.57
4 (10 × 20)	20376	103*M*	67	45522	32*M*	123.41	30	68.93	35000	34649	40*M*	70.05	36	61.16
5 (20 × 30)	31050	156*M*	106	66304	62*M*	113.54	51	60.26	42000	41814	86*M*	34.67	66	44.87

Table 10
Information summary of results for the numerical examples of the reduced CTP.

Scenario →	Normal			Pandemic										
	Without consideration of upper limit on transportation cost as constraint			Without consideration of upper limit on transportation cost as constraint					With consideration of upper limit on transportation cost as constraint					
#Numerical example (Size)	Best found objective function value (A)	Penalty (B)	Total no. of trips (C)	Best found objective function value	Penalty	% Increase in objective function value with respect to (A)	Total no. of trips	% Decrease in penalty with respect to (B)	Upper limit for total transportation cost	Best found objective function value	Penalty	% Increase in objective function value with respect to (A)	Total no. of trips	% Decrease in penalty with respect to (B)
1 (4 × 5)	665	21*M*	15	923	11*M*	38.80	10	47.62	800	778	12*M*	16.99	10	33.33
2 (5 × 10)	1000	31*M*	21	1341	18*M*	34.1	17	41.94	1250	1214	19*M*	21.4	16	23.81
3 (10 × 10)	962	41*M*	26	1818	19*M*	88.98	19	53.66	1250	1248	23*M*	29.73	18	30.77
4 (10 × 20)	1779	58*M*	37	2815	33*M*	58.23	31	43.10	2300	2296	38*M*	29.06	33	10.81
5 (20 × 30)	2775	108*M*	70	4481	64*M*	61.48	54	40.74	3550	3536	69*M*	27.42	49	30.0

Table 11
Average computational time (in CPU seconds).

Scenario →	Normal			Pandemic					
Cost function → # Numerical example (↓)	Classical	Linear fixed-charge	Non-linear fixed-charge	Classical	Linear fixed-charge	Non-linear fixed-charge	Classical	Linear fixed-charge	Non-linear fixed-charge
1	0.74	0.78	1.11	0.76	0.77	1.08	0.77	0.89	1.05
2	4.47	1.49	4.77	4.37	1.62	4.38	4.41	1.59	4.70
3	13.63	4.26	14.17	13.34	4.17	13.63	13.54	4.10	13.78
4	32.96	22.26	34.92	33.19	22.12	33.53	32.86	21.99	33.71
5	144.72	193.43	286.67	142.59	192.24	260.19	143.70	193.17	267.18

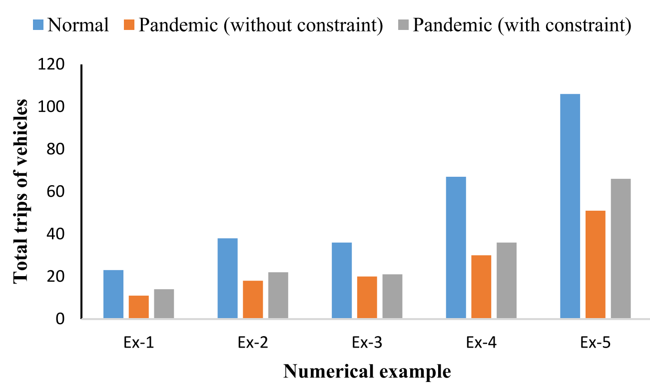

Fig. 6. Variation of total number of trips corresponding the three problems for each numerical example.

tables. The result shows that the penalty value is less for the FCTP with constraint as compared to normal scenario, and thus, the trips are restricted to less number between regions with higher restrictions for the proposed FCTP with constraint. The penalty value further decreases for the FCTP without the constraint, and hence, the number of trips between regions with higher restrictions is further less. This is due to either of the two reasons (i) availability of alternate origin–destination pairs with less restrictions, or (ii) availability of alternate origin–destination pairs with lesser difference in LSR values. For each numerical example, the total transportation cost corresponding to the three problems is presented in Fig. 5, whereas, the total number of trips corresponding to the problems is presented in Fig. 6, considering the quadratic fixed-charge form of cost function. The average computational time (in CPU seconds) for each instance of the numerical examples are given in Table 11.

5.4. Performance comparison

To compare the results obtained using our algorithm with existing works, we consider the problem in normal scenario, and only type of vehicle is available at each origin. Moreover, it is also considered that a vehicle can take one trip at most to a destination. In this paper, we compare the results obtained using our algorithm with the works of Jo et al. [11], Xie and Jia [13] and Lofti & Tavakkoli-Moghaddam [14]. We also compare the computational time, wherever possible.

For each numerical example of the above mentioned works, we consider the cost function to be linear and non-linear (quadratic). A comparison of results for the numerical examples given in Jo et al. [11] and Xie and Jia [13] with priority-based genetic algorithm (pb-GA), spanning-tree genetic algorithm (st-GA) and LINGO software are presented in Table 12 and Table 13, respectively. A comparison of the best, average and worst objective function value(s) corresponding to the best solution among our algorithm, pb-GA and st-GA for the numerical examples given in Lofti & Tavakkoli-Moghaddam [14] are presented in Tables 14–15. Due to randomness nature of Genetic Algorithms, our algorithm is run 10 times for each numerical example. The average computational time (ACT) (in CPU seconds) for the numerical examples of Lofti & Tavakkoli-Moghaddam [14] using our algorithm are also presented in Tables 14–15. The priority-based encoding of the solutions obtained for the numerical examples in [14] using our algorithm are presented in Table 16. In each of

Table 12
Comparison of results for the numerical examples from Jo et al. [11].

Algorithm(s)	Linear FCTP		Non-linear FCTP	
	Size of problem			
	4 × 5	5 × 10	4 × 5	5 × 10
st-GA [13]	1,642	6,696	**37, 090**	**304,200**
Pb-GA [14]	**1,484**	**6,195**	38,282	**304,200**
LINGO	**1,484**	**6,195**	**37,090**	**304,200**
Our proposed algorithm	**1,484**	**6,195**	**37,090**	**304,200**

Table 13
Comparison of results for the numerical examples from Xie et al. [13].

Algorithm(s)	Linear FCTP		Non-linear FCTP	
	Size of problem			
	8 × 16	20 × 20	8 × 16	20 × 20
st-GA	–	–	805941	3878824
Pb-GA	–	–	–	–
LINGO	54,570	–	–	–
Our proposed algorithm	**43,395**	**1,66,366**	**712542**	**3767542**

the Tables 12–15, the best among the compared approaches are shown in bold. Moreover, since the dataset (variable and fixed cost) for the numerical examples solved in the work by Balaji et al. [16] are not given, we could not compare the performance of our algorithm with theirs.

Table 12 reveals that our proposed algorithm is able to attain the best solution available in the literature corresponding to the linear and non-linear (quadratic) cost function for the numerical examples of size 4 × 5 and 5 × 10 (Jo et al. [11]). The same set of solutions are also obtained using the LINGO software. It is also seen, for the numerical example of size 4 × 5 with non-linear (quadratic) cost function, the worst solution is obtained using the pb-GA. Moreover, for each numerical example corresponding to the linear and non-linear (quadratic) cost function, the worst solution is obtained using the spanning-tree genetic algorithm (st-GA), except for the numerical example of size 4 × 5 with non-linear (quadratic) cost function.

From Table 13, it is observed that our proposed algorithm produces the best solutions corresponding to linear and non-linear (quadratic) form of the cost function for each numerical example. The LINGO software is able to solve the numerical example of size 8 × 16 with linear cost function only. The solutions obtained using st-GA for the numerical examples of size 8 × 16 and 20 × 20 with non-linear cost function are the worst among all the compared algorithms. Since the running time and performance statistics such as, average and worst objective function values for the works of Jo et al. [11] and Xie and Jia [13] are not reported, we only compare the best solutions.

From Table 14, it is observed that for the same parameter settings, our algorithm is able to attain the existing best solutions for the numerical examples of size 5×10, 10×20 and 20 × 30 with linear cost function. For the other numerical examples of size 4×5, 10×10 and 30 × 50 with linear cost function, our algorithm produces better solutions. However, our algorithm produces better solutions than the best known solutions for each numerical example with non-linear (quadratic) cost function, and are reported in Table 15. For each numerical example corresponding to linear and non-linear cost function, the average of the objective function values in 10 consecutive runs obtained using our proposed algorithm are better than the st-GA. When compared with pb-GA, the average objective function value is better for some numerical examples only corresponding to linear cost. However, better average objective function value is obtained for each numerical example corresponding to the non-linear cost. The worst among the solutions in 10 consecutive runs are obtained for each numerical example, which shows that for the linear cost, the worst objective function value obtained using our algorithm is less only for the numerical example of size 20 × 30. But, for the non-linear cost function, the worst objective function value obtained using our algorithm is least for each numerical example. From Tables 14–15, it is seen that though the average computational time (ACT in seconds) for our algorithm is marginally higher than pb-GA, it is much less than st-GA.

6. Conclusion

In the recent COVID-19 pandemic, most countries categorized regions in different groups and imposed restrictions of different levels in the movement of vehicles (which includes freight vehicles). The level of restriction in a region is based upon many factors that includes number of active cases, population density, number of migrant workers, etc. Consequently, in this scenario, transportation of items is a challenging task for the transportation companies. In this paper, we presented a model of FCTP for a homogeneous item suitable for pandemic scenario, in which multiple vehicles are available at each origin, each with different capacity, and each vehicle is allowed to take multiple trips to one or more destinations. The aim of this problem is to obtain minimum cost transportation plan from a set of origins to a set of destinations situated in regions with different levels of restrictions, so that the number of trips of vehicles moving between regions with higher levels of restrictions (i.e., higher LSR values) is less. For this, a penalty is imposed in the objective function for each such trip. Since the reduction in trips may increase the

Table 14
Comparison of results for the numerical examples from Lofti & Tavakkoli-Moghaddam [14] of linear FCTP.

# Problem	Size of problem	Parameters used		St-GA				Pb-GA				Our proposed algorithm			
		popsize	maxgen	Best	Average	Worst	ACT (in seconds)	Best	Average	Worst	ACT (in seconds)	Best	Average	Worst	ACT (in seconds)
1	4 × 5	10	500	9291	9364	9486	4.875	9291	9295	**9304**	3.25	**9168**	**9253.0**	9338	4.65
2	5 × 10	20	500	12899	13481	13996	11.54	**12718**	**12734**	**12818**	5.81	**12718**	12840.4	13009	5.96
3	10 × 10	30	500	14844	15621	16222	62.63	13987	14074	**14113**	23.62	**13934**	**14072.6**	14192	26.74
4	10 × 20	30	700	26036	27260	28309	180.8	**22095**	**22284**	**22656**	62.79	**22095**	22428.2	23200	68.84
5	20 × 30	30	700	44453	45473	45988	472.7	**32526**	**33796**	**34843**	136.2	**32526**	**33796**	**34843**	157.6
6	30 × 50	50	1000	76738	77777	78706	2893.1	55143	**55912**	**56731**	721.5	**55143**	56433.6	61506	853.5

Table 15
Comparison of results for the numerical examples from Lofti & Tavakkoli-Moghaddam [14] of non-linear FCTP (quadratic cost function).

# Problem	Size of problem	Parameters used		St-GA				Pb-GA				Our proposed algorithm			
		Popsize	Maxgen	Best	Average	Worst	ACT (in seconds)	Best	Average	Worst	ACT (in seconds)	Best	Average	Worst	ACT (in seconds)
1	4 × 5	20	500	77,798	78,270	78,479	9.938	78,458	78,458	78,458	6.314	**48490**	**50089.6**	**51386**	6.314
2	5 × 10	30	500	67,854	72,659	77,016	37.199	63,571	65,596	66,067	17.998	**51839**	**52304.8**	**52973**	17.998
3	10 × 10	30	500	63,469	68,345	71,537	62.755	55,075	55,342	55,846	25.149	**48105**	**48655.4**	**49114**	25.149
4	10 × 20	30	500	128,655	134,559	140,397	133.96	96,161	97,673	100,081	46.0	**80884**	**82677.6**	**84119**	46.0
5	20 × 30	50	1000	189,109	198,289	208,863	1176.1	126,462	128,056	129,879	325.36	**113108**	**114450.4**	**115966**	325.36
6	30 × 50	50	1000	397,082	406,872	414,957	2870.4	226,679	229,265	233,888	723.15	**195264**	**200334.8**	**204067**	723.15

Table 16
Priority-based representation of best solutions obtained using our proposed algorithm.

Problem	Solution
1L[a]	8-9-2-6-3-4-5-7-1
1L[b]	5-8-9-7-2-1-4-6-3
2L[a]	11-13-7-2-9-15-5-4-14-12-6-1-10-3-8
2L[b]	8-12-11-4-2-13-15-6-14-9-7-10-1-3-5
3L[a]	18-3-19-2-7-12-20-9-15-5-8-16-10-14-6-1-13-4-11-17
3L[b]	7-17-3-12-2-20-14-10-9-13-16-11-4-19-18-6-15-5-1-8
4L[a]	24-2-25-14-7-27-5-13-26-23-12-29-28-19-16-21-15-8-11-30-18-22-3-4-6-1-10-17-20-9
4L[b]	30-10-17-7-2-23-27-6-16-11-8-14-24-13-22-5-18-26-25-29-12-21-1-3-19-9-20-28-15-4
5L[a]	6-45-32-21-44-50-46-27-38-22-13-8-12-29-2-34-43-17-40-48-42-10-25-41-49-36-20-16-4-28-18-35-3-11-19-9-26-47-33-39-7-24-1-30-14-15-31-23-5-37
5L[b]	24-46-22-5-45-38-3-37-34-30-2-35-40-20-36-15-44-43-7-49-42-32-18-41-50-26-10-11-28-13-1-23-12-33-6-31-39-48-14-25-29-27-47-9-4-16-21-8-19-17
6L[a]	5-34-42-2-52-80-27-24-23-74-69-59-16-40-61-44-30-9-77-78-72-10-55-7-79-57-51-21-67-75-15-62-48-76-45-19-68-41-54-66-18-32-63-58-29-53-56-71-12-36-39-50-3-6-64-1-37-47-43-14-33-49-22-38-35-26-20-4-28-60-46-70-11-31-73-25-17-8-65-13
6L[b]	32-28-38-8-70-80-74-78-2-23-63-69-64-77-59-11-16-62-46-79-67-57-9-65-75-19-52-30-58-71-66-53-56-73-44-3-6-72-14-61-51-26-49-36-68-35-48-39-42-21-50-31-24-76-40-12-34-43-5-33-15-4-22-54-7-10-55-1-27-20-45-25-47-29-13-37-41-17-60-18

[a]Linear FCTP.
[b]Non-linear FCTP.

Table A.1
Variable cost matrices (for unit quantity) corresponding to the TP with 20 origins, 30 destinations and 2 vehicles at each origin.

Vehicle 1

5	7	5	7	12	11	6	9	6	6	6	4	6	6	7	12	12	9	11	11	5	11	12	9	6	4	10	7	8	12
5	10	6	5	11	5	10	11	8	11	5	9	11	7	11	12	4	10	7	12	8	8	8	5	12	8	4	9	9	8
8	9	5	8	10	10	7	7	9	10	5	10	6	10	11	11	8	9	8	11	6	10	4	10	12	12	12	12	8	9
5	10	5	5	12	11	11	7	12	7	4	12	11	4	7	7	11	9	4	4	5	6	10	4	11	7	10	10	4	6
6	6	10	7	7	10	12	12	11	10	7	11	7	12	9	10	7	7	7	7	7	6	7	11	6	5	6	4	12	6
4	5	6	10	7	7	5	4	7	12	10	8	8	4	5	4	9	8	5	10	9	6	12	4	5	6	5	5	4	4
5	4	4	6	8	7	9	10	5	10	7	12	5	12	10	7	10	6	9	12	12	6	5	10	4	4	12	5	12	12
4	5	10	11	7	5	12	12	9	4	10	4	12	9	10	8	10	5	10	7	4	8	7	4	5	7	11	11	6	11
8	6	12	5	11	4	4	10	10	10	11	5	8	8	11	12	12	6	4	8	7	12	12	10	10	11	11	8	7	5
4	9	5	10	8	4	10	8	10	8	12	6	9	5	11	5	4	10	8	12	5	11	11	11	7	8	7	5	10	10
4	11	6	4	8	10	4	4	4	8	8	12	11	4	12	7	4	10	4	8	9	4	4	5	9	7	7	4	7	5
8	5	10	9	5	12	4	12	12	4	6	5	11	4	6	10	5	4	7	12	6	11	12	6	12	7	8	7	5	9
6	7	10	12	12	12	11	4	9	9	11	11	10	9	9	10	4	10	10	8	10	12	6	7	4	5	8	6	6	9
11	8	4	8	7	10	5	4	8	11	7	7	9	4	10	4	9	11	10	4	4	7	11	6	9	11	5	4	4	6
8	9	10	8	11	12	12	11	10	8	9	4	11	12	11	6	10	7	4	8	6	4	9	4	4	5	11	4	4	9
6	8	12	12	10	10	9	9	8	6	11	11	4	7	9	12	10	6	4	10	8	6	11	5	4	9	4	9	9	4
5	11	6	11	9	12	9	12	7	11	6	5	8	6	9	4	12	6	4	11	12	9	11	8	8	12	5	8	8	8
7	8	5	9	6	10	7	9	7	10	6	9	11	10	10	7	8	7	9	6	5	7	9	4	9	4	10	10	7	5
4	8	7	5	4	8	9	5	11	12	11	4	9	8	8	4	9	10	7	4	4	9	7	9	7	12	8	4	8	11
12	8	6	7	7	4	9	12	6	7	11	11	8	5	4	12	5	10	8	9	10	8	12	11	11	6	8	6	4	12

Vehicle 2

4	12	5	4	4	8	5	9	5	5	4	4	10	6	5	11	12	5	6	7	8	12	11	5	8	8	5	12	10	5
12	9	11	11	7	12	5	6	6	6	5	4	6	12	6	6	8	6	5	8	7	9	5	4	8	9	8	9	8	12
10	5	8	8	4	10	5	5	12	6	5	5	6	6	11	9	8	4	9	7	8	12	10	9	12	5	5	5	10	7
5	5	9	7	7	7	4	9	8	4	9	7	12	11	9	10	5	4	8	8	5	12	6	11	6	5	12	5	5	7
8	6	8	11	9	12	5	10	6	7	8	11	11	7	9	7	11	9	6	6	4	7	12	6	6	12	6	12	4	7
7	8	7	11	7	12	10	6	7	10	10	11	8	8	12	5	11	8	8	11	8	6	6	5	9	6	4	9	12	4
10	4	7	4	10	8	10	5	10	5	12	7	10	7	9	8	6	6	12	10	4	6	4	4	7	7	4	8	10	4
8	7	4	9	5	8	4	11	10	11	10	9	12	8	12	9	10	6	11	7	10	9	9	10	10	4	11	8	6	8
8	8	9	7	5	10	11	5	9	8	10	4	11	8	8	11	4	12	11	9	7	8	5	12	6	9	10	11	5	12
7	7	6	12	8	7	8	5	6	11	7	11	11	6	6	5	4	6	4	11	9	7	6	8	5	6	12	9	12	4
7	6	5	9	12	8	10	7	9	12	5	12	10	11	5	12	12	12	12	10	8	6	12	9	11	4	9	10	9	8
8	10	10	7	6	8	11	12	9	7	10	9	5	7	7	4	5	4	4	4	10	6	5	9	11	12	7	8	7	4
12	9	8	8	12	11	12	9	8	6	10	5	11	11	9	5	12	8	5	10	6	10	12	7	6	11	6	10	4	7
8	12	10	12	5	8	8	4	4	4	5	10	5	12	9	8	5	6	12	4	12	6	10	9	9	11	7	10	6	7
11	8	5	9	5	6	4	10	5	11	8	6	8	9	5	11	12	4	11	9	12	8	11	7	5	6	5	6	10	5
10	8	9	9	11	11	11	9	8	10	7	10	12	12	6	12	8	12	10	7	9	9	11	5	4	10	7	12	4	11
12	8	7	8	4	12	4	9	9	6	7	12	12	4	9	6	10	5	12	8	6	8	11	11	8	11	9	11	9	9
10	8	4	11	10	11	10	11	7	4	4	8	4	4	7	9	4	4	8	12	6	8	6	5	7	10	10	10	6	4
6	10	6	4	6	4	11	4	11	5	11	9	8	11	9	11	6	7	9	8	7	10	4	7	11	5	11	6	11	4
7	4	11	9	4	4	7	9	11	5	8	8	9	12	6	5	8	6	7	12	11	8	9	9	11	5	10	9	5	8

transportation cost to unrealistic bounds, a constraint is imposed considering an upper limit on transportation cost. The problem is then solved using a genetic algorithm based approach. For this, a new crossover and a new mutation are developed to deal with multiple trips of vehicles moving to one or more destinations. The datasets for five numerical examples are generated artificially, in which the regions are categorized in three different groups. The regions are marked in Red, Orange and Green in the decreasing order of level of restriction. For each numerical example, the cost function is taken to be in three different forms, namely, linear fixed-charge, non-linear fixed-charge and classical. To prove the effectiveness of the imposed constraint, each numerical example

Table A.2
Fixed-charge matrices corresponding to the TP with 20 origins, 30 destinations and 2 vehicles at each origin.

Vehicle 1																													
85	115	90	55	105	105	120	100	120	115	125	95	100	80	55	80	125	65	55	110	60	70	70	115	85	65	90	85	50	60
60	80	110	95	120	90	110	55	110	70	85	95	50	75	100	55	50	120	60	95	100	55	50	90	110	50	60	70	80	70
120	125	125	100	60	50	80	70	55	65	100	55	105	60	110	65	110	100	115	105	105	105	100	80	125	90	110	80	125	90
55	85	100	95	95	75	125	65	120	70	50	80	70	70	85	120	85	60	80	85	125	55	90	75	100	70	70	95	95	110
95	75	55	125	65	80	120	115	100	50	100	50	55	95	80	85	50	125	50	95	65	65	75	105	55	75	125	90	125	85
95	80	80	100	60	105	55	95	110	75	110	80	115	100	60	60	125	60	110	110	120	80	85	75	55	50	50	85	80	90
60	65	60	75	60	55	105	55	70	60	110	55	100	105	90	105	125	100	60	55	55	90	85	100	125	125	55	95	85	115
75	95	65	75	55	110	85	110	110	90	85	85	85	65	50	105	70	95	75	110	50	80	115	70	115	70	65	95	90	75
90	125	50	75	60	100	105	100	75	55	100	65	50	80	85	65	100	110	85	50	60	115	100	65	70	50	105	100	55	70
115	80	95	50	70	90	105	60	105	85	105	115	100	120	95	60	110	100	110	70	115	95	60	120	65	110	100	55	65	55
65	55	115	75	80	100	80	110	55	95	125	120	120	125	110	110	60	120	85	95	115	65	85	115	95	90	105	125	70	105
125	65	60	50	70	80	100	60	85	90	75	75	95	90	65	55	90	55	65	60	95	85	60	85	105	95	55	125	65	95
90	70	100	100	80	70	85	65	75	70	95	120	100	60	60	55	65	100	100	100	50	125	90	65	105	115	65	115	85	105
100	60	50	100	55	100	65	105	115	90	65	105	50	65	70	55	105	110	55	85	105	70	100	85	105	120	80	50	125	120
65	60	70	85	70	80	125	105	90	50	55	125	85	120	70	80	115	60	80	80	85	90	90	115	70	70	100	115	60	75
85	110	70	75	90	85	95	60	60	55	115	110	95	90	65	60	90	115	125	105	115	70	50	75	70	105	100	95	125	120
110	100	125	75	90	65	125	105	110	70	85	65	80	75	100	85	60	120	80	125	50	80	95	120	50	85	65	95	70	110
120	95	60	55	95	105	50	80	50	115	95	90	125	60	115	60	65	105	55	50	100	55	105	60	125	110	75	65	85	70
70	120	60	125	80	115	90	115	85	115	120	105	55	70	65	105	65	125	70	90	105	105	75	75	85	125	110	90	80	60
80	125	90	125	100	85	115	90	90	105	55	60	60	95	90	55	95	95	110	115	110	125	75	105	70	105	120	50	90	90
Vehicle 2																													
94	121	99	61	112	112	128	109	126	125	134	100	107	85	63	85	133	71	63	115	69	80	79	120	94	72	100	95	58	67
67	88	117	101	130	97	119	62	119	76	95	101	57	83	107	61	59	125	65	102	106	64	58	98	119	55	65	78	89	80
127	130	132	108	70	59	87	79	63	73	109	63	110	69	120	70	118	105	122	115	115	111	105	87	135	97	117	90	134	98
64	93	106	102	101	84	131	73	130	77	56	88	77	80	93	126	92	69	88	94	135	63	97	81	109	78	75	102	100	115
105	82	60	133	74	85	127	120	106	58	108	57	64	103	90	91	55	132	60	102	70	75	81	113	62	85	135	95	131	92
102	85	86	109	66	114	61	103	119	83	120	89	121	108	67	69	135	66	115	115	129	89	95	85	60	57	56	95	89	96
65	75	68	83	69	62	114	63	76	68	116	64	106	114	99	110	133	106	66	61	63	98	91	106	133	132	61	103	90	121
83	100	70	83	61	120	94	117	120	99	91	95	92	72	57	115	80	101	83	117	60	90	120	79	123	75	74	103	99	80
95	131	58	85	70	107	111	108	82	63	105	70	60	87	92	75	105	116	91	56	65	120	107	71	75	56	110	108	64	80
121	85	101	58	75	99	112	65	111	90	114	121	107	125	102	67	118	108	116	78	124	103	65	130	73	118	105	63	71	64
72	65	120	85	89	108	85	116	62	105	133	129	130	131	118	117	66	127	91	100	120	75	90	124	100	100	115	134	78	111
130	74	67	59	79	89	105	68	92	96	82	81	100	96	70	62	96	63	74	67	104	90	67	93	111	103	62	132	72	102
95	80	107	106	85	80	90	70	85	78	103	127	107	68	67	63	75	108	107	109	59	134	96	75	115	124	74	123	91	111
107	65	55	106	64	106	70	111	123	98	73	110	59	71	80	61	115	116	61	94	115	80	109	95	114	126	87	56	130	129
71	70	80	91	75	88	134	112	96	60	60	133	93	130	76	85	121	65	86	87	95	97	99	121	77	80	109	123	67	82
94	118	79	84	98	93	102	67	68	62	122	115	101	99	73	68	100	120	130	110	121	76	56	82	78	114	108	105	135	125
115	105	135	85	100	74	131	112	120	76	95	73	90	81	109	90	65	127	88	131	58	86	102	129	59	92	70	105	75	120
127	101	70	64	101	113	59	87	58	125	104	99	133	65	123	65	71	110	63	58	107	60	110	67	135	118	81	73	94	75
78	126	65	131	87	124	95	123	93	121	130	111	62	76	74	113	74	134	77	99	113	110	80	81	95	134	120	96	87	66
85	130	97	131	108	94	120	98	99	112	65	65	68	100	97	63	101	101	119	124	115	130	84	111	79	114	130	56	98	99

is solved without considering the constraint. The results show that the constraint is effective in reducing the transportation cost. Thereafter, the numerical examples are solved considering the problem in normal scenario, and a comparison of results with the earlier two problems is made in terms of transportation cost and number of trips between regions with higher level of restrictions. The results show that the transportation cost is least for the transportation problem in normal scenario, whereas, the total number of trips of all the vehicles moving between regions with level of restriction high is least for the transportation problem in pandemic scenario without any constraint on transportation cost.

Scope of future work

In future, one may be consider one or more of the following natural extensions of the problem solved in this paper.

(i) Formulating a transportation problem for multiple items in pandemic scenario, in which items are categorized in different groups based on priority (For example, medicinal items may be given the top priority, the items related to grocery may be given the next priority and the items related to electronics and cosmetics may be given the last priority), and items need to be delivered at destinations maintaining the order of priority.
(ii) Setting a restriction on the amount of an item a consumer can order from an origin (producer).
(iii) Setting a restriction on the maximum number of origins (producer) from which a consumer may order.
(iv) Consideration of transshipment problems (such as [45–47] etc.) through the origin and consumer nodes.

Apart from these, one may develop some other heuristics (such as Particle Swarm Optimization [48], Ant Colony Optimization [49], Whale Optimization [50] or some other heuristic/metaheuristic algorithm) and compare the result with that obtained in this paper. While comparing the results with other heuristics, the same crossover and mutation proposed may be used or some other genetic operators may be newly developed.

CRediT authorship contribution statement

Amiya Biswas: Conceptualization, Methodology, Resources, Writing – original draft. **Sankar Kumar Roy:** Writing – review & editing, Formal analysis, Supervision. **Sankar Prasad Mondal:** Methodology, Review & validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Tables A.1 and A.2.

References

[1] F.L. Hitchcock, The distribution of a product from several resources to numerous localities, J. Math. Phys. 20 (1941) 224–230.
[2] H. Arsham, A.B. Kahn, A simplex-type algorithm for general transportation problems: An alternating to stepping-stone, J. Oper. Res. Soc. 40 (1989) 581–590.
[3] H.L. Bhatia, K. Swarup, M.C. Puri, Time-cost trade-off in a transportation problem, Opsearch 13 (1976) 129–142.
[4] A. Charnes, W.W. Cooper, The stepping stone method of explaining linear programming calculations in transportation problems, Manage. Sci. 1 (1954) 49–69.
[5] H.M. Wagner, On a class of capacitated transportation problems, Manage. Sci. 5 (3) (1959) 304–318.
[6] W.M. Hirsch, G.B. Dantzig, Notes on linear programming, Part XIX: The fixed charge problem, in: Rand Corporation Memorandum Number 1383, Santa Monica, California, 1954.

[7] M.L. Balinski, Fixed-cost transportation problems, Nav. Res. Logist. Q. 8 (1) (1961) 41–54.
[8] M. Hajiaghaei-Keshteli, S. Molla-Alizadeh-Zavardehi, R. Tavakkoli-Moghaddam, Addressing a nonlinear fixed-charge transportation problem using a spanning tree-based genetic algorithm, Comput. Ind. Eng. 59 (2) (2010) 259–271.
[9] M.M. El-Sherbiny, R.M. Alhamali, A hybrid particle swarm algorithm with artificial immune learning for solving the fixed charge transportation problem, Comput. Ind. Eng. 64 (2) (2013) 610–620.
[10] M. Gen, Y. Li, K. IDA, Spanning tree-based genetic algorithm for bicriteria fixed charge transportation problem, J. Jpn. Soci. Fuzzy Theory Syst. 12 (2) (2000) 295–303.
[11] J. Jo, Y. Li, M. Gen, Nonlinear fixed charge transportation problem byspanning tree-based genetic algorithm, Comput. Ind. Eng. 53 (2007) 290–298.
[12] S. Molla-Alizadeh-Zavardehi, M. Hajiaghaei-Keshteli, R. Tavakkoli-Moghaddam, Solving a capacitated fixed-charge transportation problem by artificial immune and genetic algorithms with a Prüfer number representation, Expert Syst. Appl. 38 (8) (2011) 10462–10474.
[13] F. Xie, R. Jia, Nonlinear fixed charge transportation problem by minimum cost flow- based genetic algorithm, Comput. Ind. Eng. 63 (2012) 763–778.
[14] M.M. Lofti, R. Tavakkoli-Moghaddam, A genetic algorithm using priority-based encoding with new operators for fixed charge transportation problems, Appl. Soft Comput. 13 (5) (2013) 2711–2726.
[15] M. Gen, F. Altiparmak, L. Lin, A genetic algorithm for two-stage transportation problem using priority-based encoding, OR Spectrum 28 (3) (2006) 337–354.
[16] A.N. Balaji, J.Mukund. Nilakantan, I. Nielsen, N. Jawahar, S.G. Ponnambalam, Solving fixed charge transportation problem with truck load constraint using metaheuristics, Ann. Oper. Res. 273 (1) (2019) 207–236.
[17] A. Biswas, A.A. Shaikh, S.T.A. Niaki, Multi-objective non-linear fixed charge transportation problem with multiple modes of transportation in crisp and interval environments, Appl. Soft Comput. 80 (2019) 628–649.
[18] K. Deb, A. Pratap, S. Agarwal, T.A.M.T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Trans. Evol. Comput. 6 (2) (2002) 182–197.
[19] S.K. Roy, S. Midya, V.F. Yu, Multi-objective fixed-charge transportation problem with random rough variables, Int. J. Uncertain. Fuzziness Knowl.-Based Syst. 26 (06) (2018) 971–996.
[20] S. Midya, S.K. Roy, Multi-objective fixed-charge transportation problem using rough programming, Int. J. Oper. Res. 37 (3) (2020) 377–395.
[21] S. Ghosh, S.K. Roy, A. Ebrahimnejad, J.L. Verdegay, Multi-objective fully intuitionistic fuzzy fixed-charge solid transportation problem, Complex Intell. Syst. 7 (2) (2021) 1009–1023.
[22] A. Biswas, T. Pal, A comparison between metaheuristics for solving a capacitated fixed charge transportation problem with multiple objectives, Expert Syst. Appl. 170 (2021) 114491.
[23] P.K. Giri, M.K. Maiti, M. Maiti, Fully fuzzy fixed charge multi-item solid transportation problem, Appl. Soft Comput. 27 (2015) 77–91.
[24] S.K. Roy, S. Midya, G.W. Weber, Multi-objective multi-item fixed-charge solid transportation problem under twofold uncertainty, Neural Comput. Appl. 31 (12) (2019) 8593–8613.
[25] S. Majumder, P. Kundu, S. Kar, T. Pal, Uncertain multi-objective multi-item fixed charge solid transportation problem with budget constraint, Soft Comput. 23 (10) (2019) 3279–3301.
[26] L. Yang, L. Liu, Fuzzy fixed charge solid transportation problem and algorithm, Appl. Soft Comput. 7 (2007) 879–889.
[27] B. Zhang, J. Peng, S. Li, L. Chen, Fixed charge solid transportation problem in uncertain environment and its algorithm, Comput. Ind. Eng. 102 (2016) 186–197.
[28] S. Molla-Alizadeh-Zavardehi, S.S. Nezhad, R. Tavakkoli-Moghaddam, M. Yazdani, Solving a fuzzy fixed charge solid transportation problem by metaheuristics, Math. Comput. Modelling 57 (5–6) (2013) 1543–1558.
[29] M.R. Safi, A. Razmjoo, Solving fixed charge transportation problem with interval parameters, Appl. Math. Model. 37 (18–19) (2013) 8341–8347.
[30] P. Kundu, S. Kar, M. Maiti, A fixed charge transportation problem with type-2 fuzzy variables, Inform. Sci. 255 (2014) 170–186.
[31] S. Ghosh, S.K. Roy, Fuzzy-rough multi-objective product blending fixed-charge transportation problem with truck load constraints through transfer station, RAIRO: Recherche OpÉ 55 (2923) (2021).
[32] J. Amankwah-Amoah, Note: mayday, mayday, mayday! responding to environmental shocks: insights on global airlines'responses to COVID-19, Transp. Res. E Logist. Transp. Rev. (2020).
[33] E. Mogaji, Impact of COVID-19 on transportation in Lagos, Nigeria, Transp. Res. Interdiscip. Perspect. 6 (2020) 100154.
[34] Z. Bian, F. Zuo, J. Gao, Y. Chen, S.S.C.P. Venkata, S.D. Bernardes, et al., Time lag effects of COVID-19 policies on transportation systems: A comparative study of New York City and Seattle, Transp. Res. A Policy Prac. 145 (2021) 269–283.
[35] K. Govindan, H. Mina, B. Alavi, A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19), Transp. Res. E Logist. Transp. Rev. 138 (2020) 101967.
[36] D. Ivanov, Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case, Transp. Res. E Logist. Transp. Rev. 136 (2020) 101922.
[37] R. Gupta, B. Rathore, B. Biswas, Impact of COVID-19 on supply chains: lessons learned and future research directions, Int. J. Qual. Reliab. Manag. (2021).
[38] A.S. Butt, Supply chains and COVID-19: impacts, countermeasures and post-COVID-19 era, Int. J. Logist. Manage. (2021a).
[39] A.S. Butt, Mitigating the effects of COVID-19: an exploratory case study of the countermeasures taken by the manufacturing industry, J. Bus. Ind. Mark. (2021b).
[40] M.N.H. Reza, S. Jayashree, C.A.N. Malarvizhi, M.A. Rauf, K. Jayaraman, S.H. Shareef, The implications of industry 4.0 on supply chains amid the COVID-19 pandemic: a systematic review, F1000Research 10 (1008) (2021) 1008.
[41] X. Shi, W. Liu, J. Zhang, Present and future trends of supply chain management in the presence of COVID-19: a structured literature review, Int. J. Logist. Res. Appl. (2021) 1–30.
[42] T.M. Choi, Innovative bring-service-near-your-home operations under corona-virus (COVID-19/SARS-CoV-2) outbreak: Can logistics become the messiah? Transp. Res. E Logist. Transp. Rev. 140 (2020) 101961.
[43] E. Hirata, T. Matsuda, Uncovering the impact of COVID-19 on shipping and logistics, Marit. Bus. Rev. (2021).
[44] H. Mollanoori, R. Tavakkoli-Moghaddam, C. Triki, M. Hajiaghaei-Keshteli, F. Sabouhi, Extending the solid step fixed-charge transportation problem to consider two-stage networks and multi-item shipments, Comput. Ind. Eng. 137 (2019) 106008.
[45] Y.T. Herer, M. Tzur, E. Yücesan, The multilocation transshipment problem, IIE Trans. 38 (3) (2006) 185–200.
[46] B. Hoppe, É. Tardos, The quickest transshipment problem, Math. Oper. Res. 25 (1) (2000) 36–62.
[47] D. Özdemir, E. Yücesan, Y.T. Herer, Multi-location transshipment problem with capacitated transportation, European J. Oper. Res. 175 (1) (2006) 602–621.
[48] J. Kennedy, R. Eberhart, Particle swarm optimization, in: Proceedings of ICNN'95-International Conference on Neural Networks, Vol. vol. 4, IEEE, 1995, pp. 1942–1948.
[49] M. Dorigo, M. Birattari, T. Stutzle, Ant colony optimization, IEEE Comput. Intell. Mag. 1 (4) (2006) 28–39.
[50] S. Mirjalili, A. Lewis, The whale optimization algorithm, Adv. Eng. Softw. 95 (2016) 51–67.