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Imprecise Modified Solid Green Traveling Purchaser Problem for Substitute Items using Quantum-inspired Genetic Algorithm

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Abstract

In the present formulation of the traveling purchaser problem (TPP), multiple vehicles exist in each market to provide transport. In addition to minimizing the total cost, a second objective is to control the total emissions for the entire process. For the transportation of goods/items after their purchase, there are two possibilities: The articles purchased at each market may be either sent to the wholesaler's warehouse depot from the market by appropriate vehicles or transported together with the purchaser for the entire route in an appropriate goods vehicle. The appropriate conveyance is chosen on the basis of its cost and greenhouse gas (GHG) emissions. The total GHG emissions for the entire route and transportation of goods is subject to a constraint and, if it is more or less than the government authorized limit, the cap-and-trade policy is followed. In this study, two substitutes were considered. To mimic the reality, the travel and transport costs are assumed to be imprecise and are introduced as fuzzy numbers. To obtain a solution, a quantum-inspired genetic algorithm (GA) (Q_iGA) was developed. This algorithm differs from others in that it includes quantum initialization, choice-based selection, and in vitro fertilization (IVF) crossover. To establish its effectiveness, a statistical test was performed. Illustrations of the models with numerical data are presented in this paper. Some managerial decisions are derived and, depending on the incentive and penalty structure for GHG emissions, a greener network design is presented to motivate the purchaser.

Keywords: Green Transportation and Routing, Traveling Purchaser Problem, Carbon credit, Quantum-inspired Genetic Algorithm,

1. Introduction

1.1. Motivation

In the classical TPP, a firm selling one or more items from a retail shop at a location employs purchasers to purchase the items from different markets and transport the items to its depot [cf. Ramesh [37]]. The purchaser starts from the depot, travels to a set of different markets, purchases the items according to their availability and the demand, and transports the goods to the depot, minimizing the combined traveling, transportation, and purchasing costs.

Previously, in developing countries, firms frequently procured items in small amounts from the markets because of inadequate appropriate storage space. The purchaser carried the goods with him/her in the same conveyance to deliver them to the depot [cf. Mansini and Tocchella [29]]. Currently, even in countries such as India and Sri Lanka, international retail houses, such as "Metro Cash and Carry" and "Reliance Fresh", do have large warehouses equipped with a food preservation facility and their purchasers make sustainable purchases of several items from remote markets, including substitutes, such as rice and wheat and different varieties of dal in large amounts. They tend to avoid large number of orders from remotely located sources for the large ordering cost and inconvenience involved, such as the unavailability of expert purchaser and the required coordination efforts. Retailers attempt to balance the problems of avoiding large ordering costs and shortages, because they lead to a loss of goodwill [cf. Report [39]]. Our examination of the purchase process revealed that, because of large bulk purchases, normally two separate vehicles are used, one to transport the goods and one to transport the purchaser. Purchasers tend to be internal employees of the firm, whereas most of the transportation operations are outsourced to a third-party transport provider.

The origin of the product complexity is the availability of substitutes offered in multiple markets together with the original product. Moreover, in a competitive market, consumer demand is influenced by the level of substitutes offered together with the original product [cf. Mcgillivray and Silver [32]]. Therefore, in the present purchaser problems, the summation of the purchasing costs of the original and substitute products together with the transportation costs is minimized.

Currently, several international bodies and government organizations are concerned about the environmental pollution caused by the emission of greenhouse gases (GHGs). This has forced businesses worldwide to adopt environment friendly green supply chain management (GSCM) to reduce CO_2 emission. In India, the transport sector accounts for 6.4% of India's Gross Domestic Product (GDP) (Road Transport Report, 2015). Very recently, a report on air pollution demand that "As high as 98% children under five years of age in low- and middle-income countries like India are exposed to toxic air, a World Health Organisation (WHO) study said. According to the study, over 1 lakh children of the same age died because of air pollution in India in 2016" [cf. WHO [48]].

This issue of environmental impact can be addressed by designing routes on the basis of acceptable emission limits, and by incorporating carbon credit/debit in transportation costs. The GHG emission of a vehicle depends on several factors, such as the speed of the vehicle, weight of a goods vehicle, and surface of the road [cf. Guo et al. [20], Dente and Tavasszy [14]]. There are two alternative modes of transportation in the procurement process. The purchaser can visit the markets and travel with the goods, but using two separate vehicles throughout the route. He/she returns to the depot as soon as the demand is satisfied. In this process, in addition to the route cost, a certain amount of GHG is emitted by both vehicles, which may lead to a carbon credit/debit. Alternatively, the purchaser can travel from market to market, whereas the goods are immediately sent to the depot from the market where they have been purchased. The latter situation may result in lower emissions, albeit it involves a compromise on transportation cost. From these two alternatives, the purchaser selects that which yields the minimum routing cost and lower total GHG emissions. This proposed problem is defined as the modified solid green traveling purchaser problem (MSGTPP).

The retail sector contributes around 10% of India's GDP and its sum is expected to reach US$ 1.3 trillion by the year 2020 according to the India Brand Equity Foundation (IBEF) Report [cf. Report [40]]. The real-life procurement problem of international retail houses after foreign direct investment (FDI) was allowed in the retail sector [cf. Nath [33]] in India motivated us to conduct the present investigation. In this study, we mathematically modeled the above problem of minimizing the total procurement cost, subject to emission constraints, and solved it using a heuristic method, a quantum-based genetic algorithm (GA), that we developed. We illustrate that the proposed solution depends on many parameters, such as the vehicles, transportation costs and rate of emission. Managers can derive the optimum decision based on the values of these parameters.

1.2. Literature Survey

The TPP, first introduced by Ramesh [37] in 1981, is a variant of the classical traveling salesman problem (TSP). Early papers on TPP include that of Voß [46], in which a study of a TPP with fixed costs was presented, and a technical report presented by Pearn [35]. Two different types of TPP models, biobjective and asymmetric, were developed by Riera-Ledesma and Salazar-González [41, 42]. A budget constraint TPP model was solved by Mansini and Tocchella [30], with capacitated and uncapacitated variations [cf. Mansini and Tocchella [29]]. Research studies on a periodic heterogeneous multiple TPP for refuge logistics and budget constraints, an uncapacitated TPP, and a multiple TPP for maximizing a system's reliability with budget constraints were reported by Choi and Lee [9, 10, 11, 12]. Other types of variations of the TPP with multiple stacks and delivery were studied by Batista-Galván et al. [4]. Although a few studies, however, a multiple vehicle TPP was papers implemented; see TPP multiple vehicles Bianchessi et al. [6], Manerba and Mansini [27], and Gendreau et al. [17]. Thus far, very few investigators have considered the emission factor in the TPP. Recently, Hamdan et al. [21] considered a green TPP as a biobjective optimization problem, minimizing both the route cost and the carbon emission due to transportation. They solved the problem by reducing it to a single objective problem with the help of weights assigned to the objectives and presented Pareto optimal solutions. A study conducted by Suzuki [44] addresses time-constrained, multiple-stop, truck-routing problem that minimizes the fuel consumption and pollutants emission. An investigation about last-mile goods movement for urban planning affecting emission was done by Wygonik and Goodchild [49]. Jevinger and Persson [24] presented a new method to understand how emissions from freight transport routes with single or several points of loading and unloading, could be allocated to individual consignments. The environmental aspect of vehicle routing problem was addressed by Masmoudi et al. [31] in the context of healthcare services. Authors illustrated the trade-off between driver wage and emission. Very recently, Alam et al. [1] proposed a comparison of route choice for navigation across air pollution depending on travel cost.

Multiple cost parameters play significant roles in determining optimal routes. The purchasing costs of items differ among markets, depending on availability, locality, etc. Traveling costs from one market to another and the transport costs entailed in sending the purchased goods from the market to the depot are controlled by the choice of appropriate vehicles, the conditions of the roads, the landscape of the areas, the seasonal conditions at the time of transportation, the load and condition of the vehicle, socio-economic conditions, etc. These exogenous factors introduce impreciseness into the cost components, and the traveling and transportation costs are thus expressed as fuzzy parameters. In studies in the literature, Angelelli et al. [2] took stochastic costs and solved dynamic TPPs. Kang and Ouyang [25] considered the stochastic prices of purchasing the products with known distributions. Recently, Beraldi et al. [5] investigated an electricity procurement plan under uncertainty in which the paradigm of joint chance constraints was adopted to define reliable plans that are feasible at a high probability level. Thus far, TPPs with imprecise traveling and transporting costs have not been solved. The proposed model examined in this study is called the imprecise modified solid green traveling purchaser problem (iMSGTPP). To overcome the fuzzy parameters, in our model we used optimistic and pessimistic methods according to Das and Maiti [13] and a credibility measure following Dubois and Prade [15].

The list of exact optimization approaches for solving a TPP includes the lexicographic search proposed by Ramesh [37], the branch-and-bound method proposed by Singh and van Oudheusden [43], the branch-and-cut approach proposed by Laporte et al. [26], Riera-Ledesma and Salazar-González [42], and Batista-Galván et al. [4], dynamic programming proposed by Gouveia et al. [19] and Kang and Ouyang [25], and constraint programming proposed by Cambazard and Penz [8]. Exact optimization approaches developed for $NP-hard$ problems typically fail to address relatively large problems because of the computation time involved. An approximation approach was investigated by Barketau and Pesch [3]. A survey of this issue was conducted by Manerba et al. [28]. To address the issue of computation time, various metaheuristic and soft computing (proposed by Zadeh [50]) approaches were explored by several researchers. Voß [47] proposed a Tabu search (TS) and simulated annealing (SA) for an uncapicitated TPP generalization with a deterministic purchasing cost. Petersen and Madsen [36] developed a heuristic approach for a multiple-stack TPP. Some other metaheuristic-based implementations include the TS method proposed by El-Dean [16], and the ant colony optimization (ACO) approach proposed by Bontoux and Feillet [7]. In the paper Jabir et al. [23], authors modelled a hybrid ACO-VNS (variable neighborhood search) based heuristics for capacitated multi-depot green vehicle routing problem. Among the metaheuristic approaches for the TPP, we found that GAs are the most widely used soft computing methods. Ochi et al. [34] proposed a parallel GA called GENPAR, based on the island model, for an asymmetric TPP. Goldbarg et al. [18] developed a transgenetic algorithm (TA) for a TPP that depends on horizontal gene transfer and endosymbiosis.

This paper's contribution to the problem context and methodology is three-fold: A) it addresses a more complex and relevant version of the TPP; B) it describes the development of a novel quantum-inspired GA-based technique that makes a methodological contribution; and C) it provides policy level insights required for robust decision support systems.

In this paper, we consider a TPP where substitute items can be purchased and vehicles of different types are available for travel and transportation under emission constraints. Goods vehicles differ in their costs per distance unit and per load unit, their capacity for carrying items, and their GHG emissions. The purchaser returns to the depot when the required items have been purchased. In this process, we calculate both the total cost and the GHG emissions due to the travel of the purchaser and transportation of goods. There are two scenarios: The goods are either transported with the purchaser or dispatched to the depot immediately after the purchase. The total cost and total GHG emissions are minimized and controlled respectively for the two scenarios. The problem comprises identifying the markets to visit, determining suitable routes for the purchaser for visiting the chosen markets, and determining the amounts of items to be purchased from the markets and sent to the depot. Here, if the emission is lower than the (government permitted) cap amount, the government gives a certain subsidy/incentive to the vendor and if it is higher, a penalty is imposed. Moreover, because of sustainable procurement planning, there is a limit on emissions, even if paying the penalty is considered worthwhile. Here, the costs of travel and goods transportation by vehicles from different markets are assumed to be imprecise and therefore are represented by fuzzy numbers. The proposed model is formulated for both scenarios. To provide a solution, in this study Q_iGA was developed and applied. Q_iGA was tested with a certain test for TPPs, and a statistical test, an ANOVA, was performed to verify its superiority. The models are illustrated with numerical examples. The solutions of different formulated models are compared. Some managerial decisions are also derived.

Thus, the main contributions of this investigation are as follows.

- The TPP is rendered more practically relevant by introducing multiple vehicle types.
- The emission factor is considered while designing the TPP network.
- The importance of the travel and transportation involved in procurement is recognized.
- The effect of substitute items is differentiated by their purchase prices.
- The impreciseness of travel and transport costs is incorporated,
- A novel quantum-inspired GA that introduces quantum-based initialization, selection, and in vitro fertilization (IVF) crossover with sigmoid mutation is developed.
- Managerial insight is extended to a policy-level decision-making framework.

This paper is structured as follows. In Section 1, a brief introduction is given. Section 2 provides more details of the TPP model with uncertain cost parameters. In Section 3, we introduce and describe in detail the development of Q_iGA. In Section 4, numerical experiments are described and the results are reported. Finally, we conclude the paper by discussing important research questions, the relevance of the insights derived in this study, and the limitations and future scope of research in Section 5.

2. Proposed Imprecise Modified Solid Green Traveling Purchaser Problem (iMS-GTPP)

2.1. Nomenclature

In Table 1, we present the notation and description of a few important parameters that we use frequently in the following sections.

2.2. Classical Traveling Purchaser Problem (TPP)

The TPP is explained as follows. Consider a depot 0, a set KR of products/items to purchase, and a set M of markets dispersed geographically. A discrete deterministic demand d_k, given for each product $k \in K$, can be shared in a subset $M_k \subset M$ of markets at a given price $p_{ik} > 0, i \in M_k$. The availability of product $q_{ik} > 0$ is given for each product $k \in K$ and each market $i \in M_k$, making it a restricted TPP. For a feasible purchasing scheme according to the product demand, the condition $\sum_{i \in M_k} q_{ik} \geq d_k, \forall k \in K$ must be satisfied. The problem is specified on a graph $G = (V, A)$, where $V = M \cup \{0\}$ is the market set and $E = \{(i, j) : i, j \in V, i \neq j\}$ is the edge set. The cost components involve the traveling cost c_{ij} for edge $(i, j) \in A$ and unit purchase cost p_{ik}. The TPP yields an output of a simple cycle in G starting and finishing at the same depot, where items are purchased at a subset of markets, to decide the amount of each product to be purchased from each market, i.e., z_{ik}, that fulfills the demand at minimum traveling and purchasing costs. For a TPP with a graph $G_\cup = (V, E)$, where $E = \{e = [i, j] : i, j \in V, i < j\}$ is the edge set and a traveling cost c_e is associated with edge set $e \in E$, let x_e, $e \in E$, $y_h \in V'$, and $h \in M$ be the decision variables taking value 1 if edge e and the corresponding market are considered, or 0 otherwise. Let also $\delta(V') :=\{(i, j) \in E : i \in V', j \in V/V'\}$ for any subset V' of nodes. The

Table 1: Notation and description of parameters and decision variables

Notation	Description
K	Product Set
M	Market Set
$C(el)$, c_{el}	Traveling cost, corresponding edge e using the l^{th} type vehicle
d_{io}	Distance from the i^{th} market to the depot
C_{io}^{ft}	Unit of transporting cost from the i^{th} market to the depot using vehicle type f
c_e^{ft}	Unit of transporting cost edge e using the f^{th} vehicle type
e_{io}^f, e_e^f, e_l^t	Emission rate of vehicle per length unit
q_{ik}	Availability of the k^{th} product at the i^{th} market
p_{ik}	Purchase cost of the k^{th} product at the i^{th} market
p_c	Possibility of crossover
p_m	Possibility of mutation
$\alpha_1, \alpha_2, \alpha_3$	Confidence level
e_{Max}	Maximum permissible emission level
d_{ik}	Demand for the k^{th} substitute item at the i^{th} market
γ, δ, η	Integrating factors of product units and distances
ξ_1	Self price impact of substitute item
ξ_2	Others price impact of substitute item
s_1	Purchase cost of substitute 1
s_2	Purchase cost of substitute 2
$\tilde{c}_{ijk}$	Fuzzy traveling cost
$\tilde{c}_{io}^{ft}$	Fuzzy transportation cost
w_i	Per unit weights of product i
x_{el}	Decision variable for traveling in the l^{th} vehicle type corresponding edge e
x_{ef}	Decision variable for transporting with the f^{th} vehicle type corresponding edge e
y_i	Decision variables of selecting the corresponding market i
$\acute{x}_{ef}$	Decision variable for transport to depot by the f^{th} vehicle type corresponding edge e

mathematical formulation is

$$\text{Minimize S} = \sum_{e\in E,} c_e x_e + \sum_{k\in K} \sum_{i\in M_k} p_{ik} z_{ik} \tag{1}$$

$$\text{subject to} \quad \sum_{i\in M_k} z_{ik} = d_k, \;\; k \in K \tag{2}$$

$$z_{ik} \leq q_{ik} y_i \;\; k \in K, i \in M_k \tag{3}$$

$$\sum_{e\in\delta(\{h\})} x_e = 2 * y_h, \;\; h \in M \tag{4}$$

$$\sum_{e\in\delta(\{h\})} x_e \leq |A| - 1, (A \subset V, 2 \leq |A| \leq M - 1) \tag{5}$$

$$\sum_{e\in\delta(M')} x_e \geq 2 * y_h, \quad M' \subseteq M, h \in M' \tag{6}$$

$$z_{ik} \geq 0, \quad k \in K, i \in M_k \tag{7}$$

$$y_i \in \{0,1\}, \quad i \in M \tag{8}$$

$$x_e \in \{0,1\}, \quad e \in E \tag{9}$$

The objective function Eq. (1) minimizes the traveling and purchasing costs. Eq. (2) ensures that the total demand for every product is satisfied. The constraint in Eq. (3) is incorporated to ensure that the products are purchased from a selected market; the purchased quantity should not overreach the availability at the corresponding market. For the graph, because of the constraint degree Eq. (4), two edges must be incident to each visited vertex. The sub-tour elimination constraint is defined by Eq. (5). We write Eq. (6) to ensure that at least two edges are incident to the subset of markets containing one at which purchases are made. The constraint in Eq. (7) denotes the purchasing unit at any market. Finally, constraint Eqs. (8)–(9) represent the binary and non-negative conditions exerted on variables.

2.3. Modified Solid Green Traveling Purchaser Problem (MSGTPP) with Substitute Items

We consider a TPP with an option to procure both regular and substitute items, where a purchaser goes to multiple markets and places orders that will be transported to the depot. Both the purchasers travel and the transportation of goods may be arranged in multiple vehicle types.

Let c_{el} define the traveling cost from the i^{th} market to the j^{th} market with $\{e = (i,j)\}$ using the l^{th} type of conveyance, $l \in \{l : 1, 2, \cdots, L\}$. Similarly, c_{i0}^{ft} identifies the unit transportation cost from the i^{th} market to depot 0 using vehicle type $f = \{f : 1, 2, \cdots, F\}$. To incorporate greenness in the routing plan, we introduce a parameter e_{i0}^{f} to indicate the amount of carbon emitted per unit distance during transportation from the i^{th} market to depot 0 by the f^{th} vehicle type. Similarly, we introduce e_e^f, which corresponds to the edge e. We define the transportation cost as d_{i0}^t, which is the distance from market $i \in M$ to depot 0; d_e^t is the corresponding transporting distance of the edge e. γ and δ are the impact factors of the emissions associated with the vehicle weight and transport distance, respectively, and e_{Max} is the maximum permissible emission level. We also consider substitutability in the problem context by considering two substitutes d_1 and d_2 of each k^{th} item with demand d_k. The demand for substitutes is dependent on self and cross price elasticity.

The mathematical formulation of a solid green TPP with substitute items is as follows.

2.3.1. Scenario I: Goods are transported directly to the depot immediately after purchase

$$\left.\begin{array}{c} S_1 = \sum\limits_{e\in E,} (c_{el}) x_{el} + \sum\limits_{k\in K} \sum\limits_{i\in M_k} p_{ik} z_{ik} \\ S_2 = \sum\limits_{e\in E} \sum\limits_{i\in M_k} c_{i0}^{ft} \acute{x}_{ef} \\ \text{Minimize } S = S_1 + S_2 \end{array}\right\} \tag{10}$$

$$\text{subject to} \quad \sum_{e\in E,k\in K}\sum_{i\in M_k}(\gamma*(z_{ik})^{\eta}+\delta*d_{i0}^{t})e_{i0}^{f}\acute{x}_{ef}+\sum_{e\in E}d_e e_l^t x_{el}\leq e_{Max} \tag{11}$$

$$\left.\begin{aligned} d_k &= d_{1k}+d_{2k}, \quad k\in K \\ d_{1k} &= d_{1kbase}-\xi_1*s_1+\xi_2*s_2, \\ d_{2k} &= d_{2kbase}-\xi_1*s_2+\xi_2*s_1, \\ \text{i.e. } d_k &= d_{1kbase}+d_{2kbase}+(\xi_2-\xi_1)*(s_1+s_2) \\ \text{where} \quad & x_{el}, x_{ef}, \acute{x}_{ef}\in\{0,1\}\text{ and } l\in\{1,2,\cdots,L\}, f\in\{1,2,\cdots,F\}. \end{aligned}\right\} \tag{12}$$

with Eqs. 3–9. Here, d_{1k} and d_{2k} are the demand for the items that can be substituted for each other, s_1 and s_2 are the purchasing costs, and d_{1kbase} and d_{2kbase} are the base demand for the items. γ, η, and δ are the emission factors associated with the product units transported and the distance of the market from depot, respectively. ξ_1 and ξ_2 are the demand elasticities of substitute items.

2.3.2. Scenario II: Goods are transported with purchaser in a separate vehicle

$$\begin{aligned} S_1 &= \sum_{e\in E,}(c_{el})x_{el}+\sum_{k\in K}\sum_{i\in M_k}p_{ik}z_{ik} \\ S_2 &= \sum_{e\in E}\sum_{i\in M_k}c_e^{ft}x_{ef} \\ \text{Minimize } S &= S_1+S_2 \end{aligned} \tag{13}$$

$$\begin{aligned} \text{subject to} \quad & \sum_{e\in E,k\in K}\sum_{i\in M_k}(\gamma*(z_{ik})^{\eta}+\delta*d_e^{t})e_e^{f}x_{ef}+\sum_{e\in E}d_e e_l^t x_{el}\leq e_{Max} \\ \text{where} \quad & x_{ef}\in\{0,1\}\text{ and } l\in\{1,2,\cdots,L\}, f\in\{1,2,\cdots,F\}. \end{aligned} \tag{14}$$

with Eqs. 3–9 and 12.

2.4. Imprecise Modified Solid Green Traveling Purchaser Problem (iMSGTPP) with Substitute Items under Fuzzy Environment

We consider travel and transportation costs as fuzzy numbers, i.e., $\tilde{c}_{ijl}$ and $\tilde{c}_{i0}^{ft}$, respectively, for Scenario I. Thus, mathematically the costs are represented as

$$\text{Minimize}S=\sum_{e\in E}(\tilde{c}_{el})x_{el}+\sum_{k\in K}\sum_{i\in M_k}p_{ik}z_{ik}+\sum_{e\in E}\sum_{i\in M_k}\tilde{c}_{i0}^{ft}\acute{x}_{ef} \tag{15}$$

with Eqs. 3–9, 11, and 12.

Since minimization of the objective under fuzzy values is not straightforward, the above problem can be reduced in deterministic forms using various approaches.

2.4.1. Possibility approaches (optimistic decision maker (ODM))

Writing the fuzzy objective in an optimistic sense using Eq. Appendix A, Eq. 15 is reduced to

$$\begin{aligned} &\text{to minimize} \quad S \\ &\text{subject to } Pos\Big(\sum_{e\in E}(\tilde{c}_{el})x_{el}+\sum_{k\in K}\sum_{i\in M_k}p_{ik}z_{ik}+\sum_{e\in E}\sum_{i\in M_k}\tilde{c}_{i0}^{ft}\acute{x}_{ef}<S\Big)\geq\alpha_1 \end{aligned} \tag{16}$$

where α_1 is a predefined level of possibility and S is a crisp value, both of which are entirely determined by the salesman, with Eqs. 3–9, 11, and 12. For the triangular fuzzy numbers (TFNs)

$\tilde{c}_{el} = (c^1_{el}, c^2_{el}$ and $c^3_{el})$, $\tilde{c}^{ft}_{i0} = (c^{1ft}_{i0}, c^{2ft}_{i0}, c^{3ft}_{i0})$.
Then, the above problem is reduced according to Lemma 2.1.a in Appendix A to

$$\begin{aligned} &\text{to minimize} \quad S \\ &\text{subject to} \ \frac{S - F_1}{F_2 - F_1} \geq \alpha_1 \end{aligned} \tag{17}$$

with Eqs. 3–9, 11, and 12,

$$\text{where } F_s = (\sum_{e \in E} (c^s_{el}) x_{el} + \sum_{k \in K} \sum_{i \in M_k} p_{ik} z_{ik} + \sum_{e \in E} \sum_{i \in M_k} c^{sft}_{i0} \acute{x}_{ef} < F), \quad s = 1, 2, 3.$$

The objective function in Eq. 17 is changed to

$$\begin{aligned} &\text{minimize} \quad F_1 + \alpha_1 (F_2 - F_1) \\ &\text{subject to} \quad \sum_{e \in E, k \in K} \sum_{i \in M_k} (\gamma * (z_{ik})^{\eta} + \delta * d^t_{i0}) e^f_{i0} \acute{x}_{ef} + \sum_{e \in E} d_e e^t_l x_{el} \leq e_{Max}, \end{aligned} \tag{18}$$

with Eqs. 3–9 and 12.

2.4.2. Necessity approaches (pessimistic decision maker (PDM))

Writing the fuzzy objective in a pessimistic sense using Eq. (2), we have

$$\begin{aligned} &\text{to minimize} \quad S \\ &\text{subject to} \quad Nec(\sum_{e \in E} (\tilde{c}_{el}) x_{el} + \sum_{k \in K} \sum_{i \in M_k} p_{ik} z_{ik} + \sum_{e \in E} \sum_{i \in M_k} \tilde{c}^{ft}_{i0} \acute{x}_{ef} < S) \geq \alpha_2 \end{aligned} \tag{19}$$

where α_2 is the predefined level of necessity, which is entirely determined by the salesman, with Eqs. 3–9, 11, and 12. Then, the above problems can be reduced according to Lemma 2.1.b in Appendix A:

$$\begin{aligned} &\text{to minimize} \quad S \\ &\text{subject to} \quad \frac{F_3 - S}{F_3 - F_2} \leq 1 - \alpha_2 \end{aligned} \tag{20}$$

with Eqs. 3–9, 11, and 12. The objective function in Eq. 20 is changed to

$$\begin{aligned} &\text{minimize} \quad F_3 + (1 - \alpha_2)(F_3 - F_2) \\ &\text{subject to} \quad \sum_{e \in E, k \in K} \sum_{i \in M_k} (\gamma * (z_{ik})^{\eta} + \delta * d^t_{i0}) e^f_{i0} \acute{x}_{ef} + \sum_{e \in E} d_e e^t_l x_{el} \leq e_{Max} \end{aligned} \tag{21}$$

with Eqs. 3–9 and 12. Here, α_2 is the predefined necessity level.

2.4.3. Credibility approach

For the model defined in Eq. 15, the crisp form according to the credibility measure given in Section Appendix A.2 is

$$\begin{aligned} &\text{to minimize} \quad S \\ &\text{subject to} \quad Cr(\sum_{e \in E} (\tilde{c}_{el}) x_{el} + \sum_{k \in K} \sum_{i \in M_k} p_{ik} z_{ik} + \sum_{e \in E} \sum_{i \in M_k} \tilde{c}^{ft}_{i0} \acute{x}_{ef} < S) \end{aligned} \tag{22}$$

with Eqs. 3–9, 11, and 12. The above Eq. 22 transformed using Eq. (5) is

$$\begin{aligned} &\text{to minimize} \quad S \\ &\text{subject to} \quad \frac{S-F_1}{2(F_2-F_1)} \geq \alpha_3 \quad if \quad F_1 \leq S \leq F_2 \\ &\frac{S-2F_2+F_3}{2(F_3-F_2)} \geq \alpha_3 \quad if \quad F_2 \leq S \leq F_3 \end{aligned} \tag{23}$$

Here, α_3 is a predefined confidence level and F is the crisp value given by the salesman, with Eqs. 3–9, 11, and 12.
Thus, the above equation can be written as

$$\begin{aligned} &\text{to minimize} \quad F_1 + 2\alpha_3(F_2 - F_1) \quad if \quad F_1 \leq S \leq F_2 \\ &\text{subject to} \quad \sum_{e\in E, k\in K} \sum_{i\in M_k} (\gamma * (z_{ik})^{\eta} + \delta * d^t_{i0}) e^f_{i0} \acute{x}_{ef} + \sum_{e\in E} d_e e^t_l x_{el} \leq e_{Max} \end{aligned} \tag{24}$$

and

$$\begin{aligned} &\text{to minimize} \quad 2F_2 + F_3 + 2\alpha_3(F_3 - F_2) \quad if \quad F_2 \leq S \leq F_3 \\ &\text{subject to} \quad \sum_{e\in E, k\in K} \sum_{i\in M_k} (\gamma * (z_{ik})^{\eta} + \delta * d^t_{i0}) e^f_{i0} \acute{x}_{ef} + \sum_{e\in E} d_e e^t_l x_{el} \leq e_{Max} \end{aligned} \tag{25}$$

with Eqs. 3–9 and 12.

3. Proposed Quantum-inspired Genetic Algorithm (Q_iGA)

We focused on heuristic approaches such as GA to address the TPP with variations because of the computational time involved. The properties of quantum mechanics motivated us to develop a quantum-inspired GA to achieve faster execution by utilizing the inbuilt properties of quantum computation. Here, we select qubits to visit each markets characteristics in the chromosomes of Q_iGA, which outperforms the classical counterpart in terms of the diversity of visiting the population of markets. The convergence of the algorithm is more rapid than that of the traditional one. In this section, some classical properties of quantum computation and its adaptation to a GA are described.

3.1. Quantum Computing

In basic quantum computing, the information is stored in quantum bits (qubits) (Han and Kim [22]). A quantum qubit represents state 1, state 0, or a superposition of both. The state of a qubit can be described as (Talbi et al. [45]):

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{26}$$

where $|0\rangle$ and $|1\rangle$ represent the classical bit values 0 and 1, respectively, with α and β complex numbers such that

$$||\alpha||^2 + ||\beta||^2 = 1 \tag{27}$$

α^2 and β^2 are the probability values of the qubit in states 0 and 1, respectively. In classical quantum computing, a quantum register with n qubits can represent 2^n different values. However, when considering the "measure", the superposition is demolished and one single value becomes accessible for use. The exponential growth of the state space with the number of particles that recommended a possible exponential speed-up of computation on quantum computers vis-a-vis classical computers.

3.2. Quantum-inspired Genetic Algorithm (Q_iGA)

Here, we propose a quantum-inspired GA (Q_iGA) that uses the quantum initialization and selection, an IVF crossover, and generation-dependent sigmoid mutation. The proposed Q_iGA and its procedures are presented below.

3.2.1. Quantum representation and initialization

The solution makes α and β dependent on the distance/cost and demand between any two markets i and j with $i, j \in M$. For an $|M| = n$ markets/nodes TPP, we consider an $n \times n$ cost/distance matrix. We compute α_{ij} using

$$\alpha_{ij} = \mu * \frac{C_{ij}}{S_i} - \nu * \frac{A_j}{SA_i}, i, j = 1, 2, \cdots, n. \tag{28}$$

To build a route in this mechanism, we incentivize the markets to be visited from the most recently visited one by considering the traveling cost and product availability. While an increase in the travel cost reduces the probability of visiting that market, an increase in availability motivates the procurement manager to include it. In Eq. 28, μ and ν are constant parameters, node i represents the most recently visited market, and node j refers to any market in the set of markets connected to market i but yet to be visited. C_{ij} is the traveling cost from the i^{th} to the j^{th} market and S_i is the sum of the traveling costs to the connected (with i) unvisited markets j. Similarly, A_j is the product availability at the j^{th} market and SA_i is the sum of the availability at the markets connected to node i but as yet unvisited. When the value of α_{ij} has been obtained, the value of β_{ij} is obtained using Eq. 27. Thus, we obtain a quantum representation of the TPP with each state represented in two qubits by an $n \times n$ matrix. Now, to find the initialized population for the GA, we convert the above qubit matrix with $0s$ and $1s$ by applying some threshold to β^2 values.

A row is randomly generated and a column on that row is randomly selected. If it is 1s, then the corresponding market is chosen; else, another column is selected. By repeating the same procedure, maintaining the TPP condition, a path that is considered a chromosome for the GA is generated.

Here, a complete route traversing $M_k (\in M)$ markets represents a solution. We represent a solution of visited markets by an M_k dimensional integer vector $X_i = (x_{i1}, x_{i2}, ..., x_{iMk})$. A number N of chromosomes for the GA is generated randomly before the GA operators are applied. The pseudocode of quantum initialization is as follows.

Step 1. Start

Step 2. Calculate α and β from Eqs. 27 and 28.

Step 3. Determine the superposition value of each qubit as follows.

if ($\beta^2 \geq$ qubit initialization threshold (predefined))

$\alpha|0\rangle + \beta|1\rangle = 1;$

else

$\alpha|0\rangle + \beta|1\rangle = 0;$

Step 4. Form the matrix of 0s and 1s.

Step 5. Each edge of a TPP has a qubit superposition $\alpha|0\rangle + \beta|1\rangle$ having a value of either 0 or 1. "1 means the edge is taken into consideration and "0 means the edge is not taken into consideration.

Step 6. For i=1 to pop-size

Step 7. Randomly select a row and randomly pick a column. If it is 1s, then choose the corresponding market. Similarly, the rest of the markets are connected according to the TPP conditions to be satisfied.

Step 8. Generate a TPP path (chromosome).

Step 9. End for

Step 10. End.

3.2.2. Quantum selection

We obtain an average value of β^2 by considering the chosen markets in a solution (chromosome). In addition, we define a threshold value of β^2 to select solutions for the mating pool, as β^2 defines the attractiveness of a market based on cost and availability. We use the set of steps below to create the mating pool:

Step 1. Start

Step 2. For i=1 to pop-size,

Step 3. Evaluate sum and average of β^2 of each path,

Step 4. If (average $\beta^2 >$ threshold value of β^2),

Select corresponding path for mating pool,

i=i+1

else

Choose the path corresponding with maximum β^2,

i=i+1

Step 5. End for

Step 6. End

3.2.3. In vitro fertilization (IVF) crossover

In our proposed IVF crossover, except for the original parents, there is one additional mother, known as a surrogate mother, who takes an active part in enhancing the diversity and solution quality of the child. Figure 1 shows a schematic view of the proposed crossover. First, we randomly select the three parents to generate two offspring using standard crossover techniques by selecting markets using the β^2 values, adhering to the TPP restriction and demand constraints. Thus, the crossover procedure is as follows.

We begin by selecting three path/solutions (parents) from the mating pool and generate a random number r in the range [0,1] with probability of crossover (p_c) exogenously defined. If $r < p_c$, then we select the corresponding solution as the first parent (say Pr_1). Similarly, we find the other two parents, i.e., Pr_2 and Pr_3.

To explain the purpose, we define the three parents as Pr_1: a_1, a_2,..., a_{M_R}; Pr_2: s_1, s_2,..., s_{M_k}, and Pr_3: r_1, r_2,..., r_{M_k}.

Here, (a_1, a_2,..., a_{M_k}), (s_1, s_2,..., s_{M_k}), and (r_1, r_2,..., r_{M_k}) are markets within (1, 2, 3,..., M). Then, we choose a market randomly from 1 to M, say $a_i = s_p = r_q$ (i, p, q=1, 2, ..., M) to modify the parents by placing a_i, s_p, or r_q in the first position of Pr_1, Pr_2, and Pr_3. Now, the modified parents are

Pr_1: a_i, a_1, a_2,.., a_{i-1}, a_{i+1},....a_{M_k}
Pr_2: s_p, s_1, s_2,., s_{p-1}, s_{p+1},...., s_{M_k}
Pr_3: r_q, r_1, r_2,., r_{q-1}, r_{q+1},...., r_{M_k}

To obtain the first child (Ch_1), we fix a_i in the first place of Ch_1. We compare the β^2 values of a_1, s_1, and r_1 to choose the next market (with the maximum β^2 value) to be visited after a_i. For example, if s_1 has the maximum β^2 value, we update the child solution as $Ch1 : a_i, s_1$. We continue this process to construct an offspring until the demand is satisfied. In each step, we concatenate a market such that the travel path satisfies the TPP restrictions. First, in each step, we check whether the market already visited is among the offspring; then, the β^2 values of the next market among the parents will be considered, i.e., repetition of the markets is not appraised. Second, the concatenation is continued until all the markets are visited or the demand is satisfied. For the next generation, we replace the first two parents by the generated offspring.

The steps of an IVF crossover algorithm are as follows.

Step 1: Start,

Step 2: Initialize the three parents (Pr_1, Pr_2, Pr_3) depending on probability of crossover p_c,

Step 3: Generate a random number between 0 and the number of markets (a_i say),

Step 4: Update the parents by placing a_i in the first position of each parent,

Step 5: The first child initiates the route with market a_i,

Step 6: Find the maximum β^2 value from a_i to the next visited market in among the three parents, i.e., a_1, s_1, r_1 in solutions Pr_1, Pr_2, Pr_3, respectively,

Step 7: Repeat Step 6 until the terminating conditions are satisfied, i.e., the demand is fulfilled or all markets have been visited,

Step 8: End.

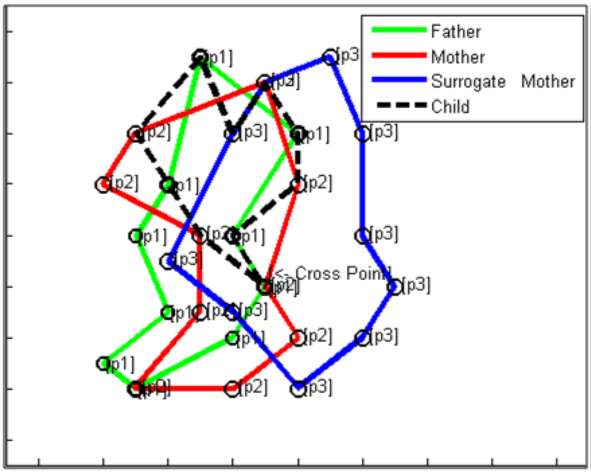


Figure 1: In vitro fertilization crossover.

3.2.4. Sigmoid random mutation

We follow the steps below for mutation.

(a) Generation dependent p_m: We acquire the probability of mutation (p_m) by

$p_m = \frac{k}{1+e^{-g}}$, k∈[0,1], where g is the current generation number.

(b) Selection for mutation: To select the chromosome for mutation, we produce a random number $r \in [0, 1]$. When $r < p_m$, the corresponding chromosome is selected for mutation. Here, p_m decreases smoothly as the generation increases. In a single point random mutation, two markets are randomly chosen from each chromosome and interchanged to create the new offspring set.

3.2.5. Procedure of $Q_i GA$

Consolidation of the above steps leads to the following Q_iGA algorithm.

Procedure name: Quantum-inspired Genetic Algorithm (Q_iGA).

Input: Max Gen, Population Size (pop_size), Probability of Crossover (p_c), Max Initialization, Problem Data (cost, availability, demand and distance matrices).

Output: Set of optimum solutions,

Step 1. Start

Step 2. Quantum initialization,

Step 3. Set initialization s ← 1,

Step 4. Check the condition **while** ($s \leq$ Max Initialization) **do** up to Step 28,

Step 5. Evaluate α and β from cost and availability matrices,

Step 6. Create the matrix of 0s and 1s with a certain threshold of α^2,

Step 7. Randomly select the row and column by choosing 1s until the demand is satisfied, and construct the path,

Step 8. Set starting generation $t \leftarrow 0$,

Step 9. Initialize population $p(t)$, where $f(x_i)$, $i = 1, 2, \cdots,$ pop_$size$ are the chromosomes, M_k numbers of the nodes in each chromosome represent a solution/path of the TPP,

Step 10. Check the condition **while** ($t \leq MaxGen$) **do** up to Step 26,

Step 11. Quantum selection procedure,

Step 12. Fix the β^2 of each chromosome of $p(t)$ according to Subsection 3.2.2,

Step 13. Generate the mating pool based on β^2,

Step 14. IVF crossover procedure,

Step 15. Select the parents depending on the value of p_c from mating pool,

Step 16. Modify the parents using crossover,

Step 17. According to Subsection 3.2.3 perform the crossover operation on selective chromosomes/ solutions,

Step 18. Generate offspring and replace it with the first two parents,

Step 19. Repeat Steps 15 to 18 depending on the value of p_c.

Step 20. Generation-dependent sigmoid mutation P according to Subsection 3.2.4,

Step 21. Evaluate $p_m=\frac{1}{1+e^{-t}}$,

Step 22. Choose the offspring for mutation based on the value of p_m,

Step 23. Exchange the place of these markets,

Step 24. Store the new offspring into offspring set,

Step 25. Compare the fitness and store the local optimum and near optimum solutions,

Step 26. $t = t + 1$,

Step 27. Repeat Steps 10 to 26,

Step 28. $s = s + 1$,

Step 29. Repeat Steps 4 to 28,

Step 30. (Optimum Solution) Store the global optimum and near optimum values,

Step 31. **Terminate**.

4. Computational Experiment on Q$_i$GA

We conducted three sets of experiments to understand the effectiveness of the proposed metaheuristic and to derive insights from the chosen problem context under the crisp and fuzzy environments. We coded the algorithm in C and C++ with the Codeblock compiler under 6th Generation Intel Core i3, CPU@3.

4.1. Testing and Some Results on Test Problems from the Traveling Salesman Problem Library (TSPLIB)

This section establishes the effectiveness of the proposed metaheuristic by comparing the results with those of the traditional GA on benchmark instances. We took standard benchmark problems from the traveling salesman problem library (TSPLIB) (Reinelt [38]) repository. We introduced the capacity (or availability) for each market by generating a random number in a range ensuring that the total depot demand could not be met by one market. Table 2 illustrates the results in terms of the solution quality and computation time. The percentage values represent the extent to which Q$_i$GA is an improvement on the traditional GA using the formula $\frac{Cost_{GA-Trad}-Cost_{Q_iGA}}{Cost_{GA-Trad}} * 100$ %, where $Cost_{Q_iGA}$ and $Cost_{GA-Trad}$ denote the costs obtained by running Q$_i$GA and the traditional GA, respectively. To obtain an effective comparison, we selected 12 benchmark problem instances with sizes from 100 to 200 nodes. The market capacity values were chosen to ensure that at least 70% of the markets should be traversed to meet the aggregate demand of the depot. The results compare the worst, average, and best costs obtained after 100 individual runs. The difference in CPU time column reports the difference in the time taken by the traditional GA and Q$_i$GA to obtain the best solution. The results clearly show that Q$_i$GA performs better than the traditional GA in terms of solution quality with a significant reduction in computation time. Table 3 summarizes the results obtained in terms of traveling and transportation costs on benchmark problems with sizes ranging from 29 nodes to 654 nodes with varying availability. We observe a significant reduction in the total cost with an increase in availability and also in graph density.

Table 2: Comparison of Q_iGA and traditional genetic algorithm on benchmark instances

Algorithm	Instance	Worst (%)	Avg (%)	Best (%)	Difference in CPU time (seconds)
Q_iGA & GA	korA100	1.23	1.04	0.05	1597
	kroB100	2.54	0.78	0.21	2198
	kroC100	0.56	0.18	0.78	2765
	kroD100	2.01	1.54	2.14	1932
	kroE100	0.75	1.102	0.49	1534
	eil101	0.015	01.25	0.001	1779
	lin105	0.075	0.012	0.045	2984
	gr120	0.048	1.023	0.851	2745
	kroA150	0.025	0.78	0.034	1956
	kroB150	0.078	0.15	0.04	3176
	ch150	0.073	0.045	0.008	2849
	gr202	1.024	0.046	0.97	4127

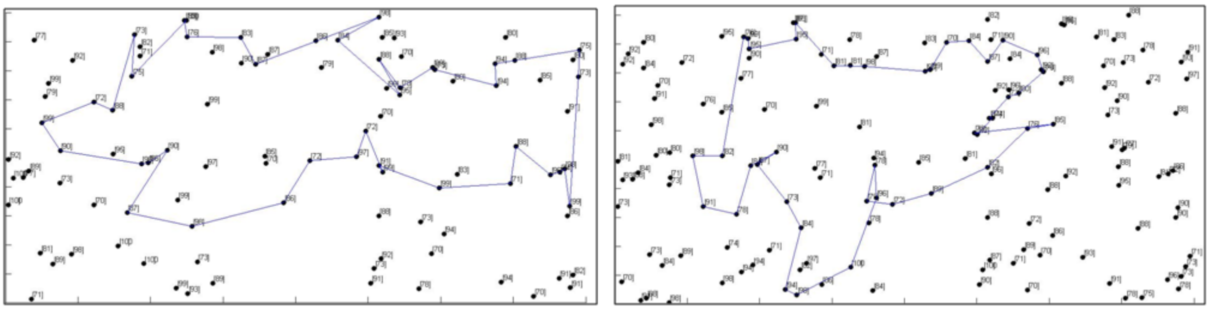
Table 3: Study of different test problems in the traveling salesman problem library

Instances	Availability (%) Increases	Transport Cost (%) Decrease	Travel Cost (%) Decrease	Objective Cost (%) Decrease
bayg29	10-100	-	-	-
	40–100	13	7	10
	70–100	32	18	23
korA100	10–100	-	-	-
	40–100	28	14	17
	70–100	41	23	27
korB100	10–100	-	-	-
	40–100	31	17	24
	70–100	46	26	31
korC100	10–100	-	-	-
	40–100	26	17	19
	70–100	39	21	27
korD100	10–100	-	-	-
	40–100	35	19	23
	70–100	47	26	35
korE100	10–100	-	-	-
	40–100	39	23	30
	70–100	56	31	47
korA150	10–100	-	-	-
	40–100	33	26	36
	70–100	59	39	56
korB150	10-100	-	-	-
	40–100	29	15	28
	70–100	67	44	58
korA200	10–100	-	-	-
	40–100	37	23	22
	70–100	53	31	47
korB200	10-100	-	-	-
	40–100	41	29	31
	70–100	63	45	55
p654	10-100	-	-	-
	40–100	43	19	35
	70–100	61	33	56

Next, we examine the change in the TPP solution with different availability levels for market selection and procurement planning. We provide the solutions obtained by Q_iGA on larger problem instances in Figures 2 and 3. In Figures 2(a) and 2(b), we see the impact of the same availability range with a much denser market (150 markets) for kora150 and observe a market network with lower traveling and transportation cost. We observe a similar phenomenon in Figure 3 with problem sizes varying from 100 markets (Figure 3(a)) to 200 markets (fig:Ava 10-100 for kora200).

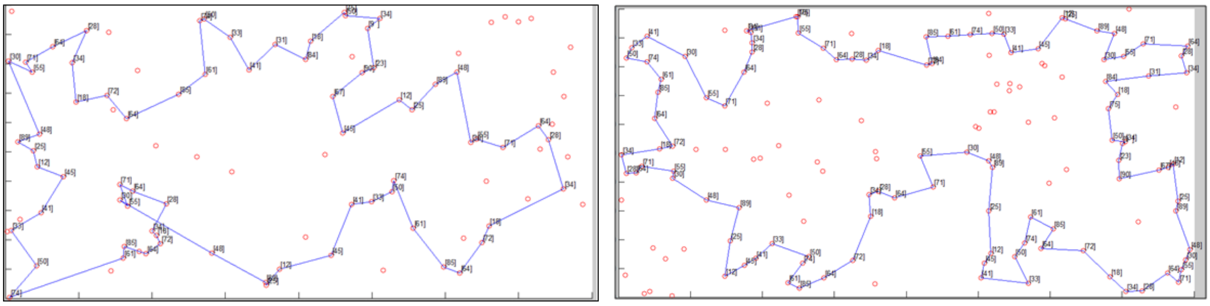
Figure 4 illustrates market selection and logistic planning with 100 and 200 nodes with substitute items. In line with our expectation, the number of markets visited does not increase proportionally with the increase in demand because of the availability of substitute items.

We observe that fewer markets are selected as the availability in every market increases. Al-

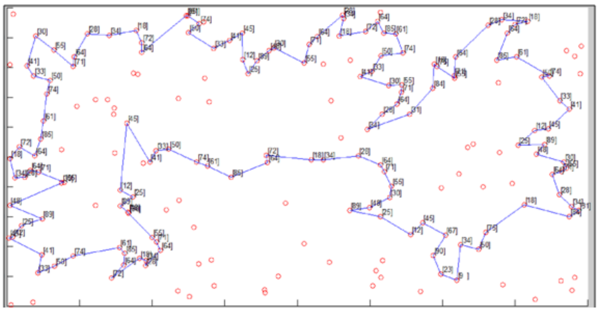


(a) Market planning for korA100 (b) Market planning for korA150

Figure 2: Market planning for 70–100 units availability



(a) Market planning for korC100 (b) Market planning for korA150

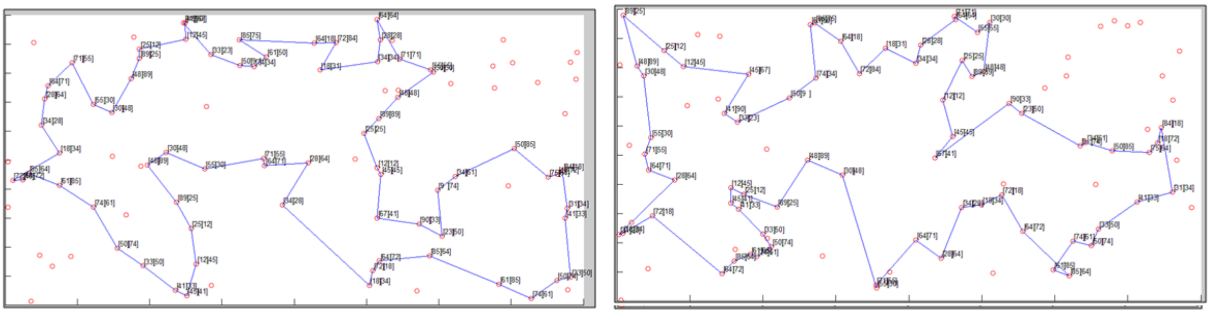


(c) Market planning for korA200

Figure 3: Market planning with 10–100 units availability for korC100, korA150, and korA200

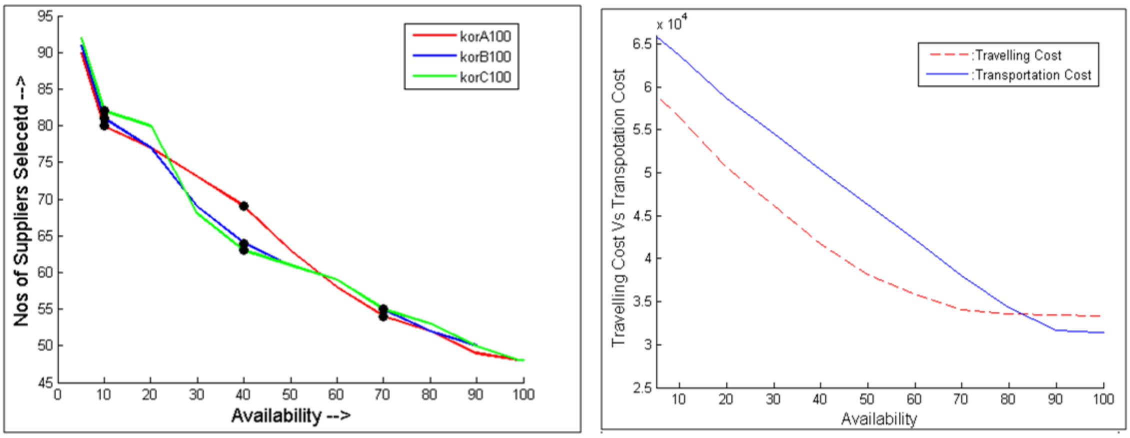
though an increase in availability involves a fixed cost for capacity expansion, a procurement manager may accrue benefits in terms of a reduction in travel and transportation cost. For the sake of brevity, we omit the results obtained for larger markets. The results/figures are recorded in the online supplement.

We conclude this section by examining how the market selection and total cost change with availability, as depicted in Figure 5. In Figure 5(a), we plot the change in the number of markets selected with the increase in availability at each market. The graph indicates a decrease in the number of markets visited with a decreasing return, i.e., the number of markets will not be reduced significantly beyond a threshold with an increase in availability. A similar observation is more evident in the plot of the traveling and transportation costs shown in Figure 5(b).



(a) Market planning for korA100 (b) Market planning for korC200

Figure 4: Market planning with substitute items for kora100, korc200



(a) Availability vs. market selection (b) Availability vs. travel and transport cost

Figure 5: Availability vs. market and cost

4.2. Imprecise Modified Solid Green Traveling Purchaser Problem in Crisp Environment

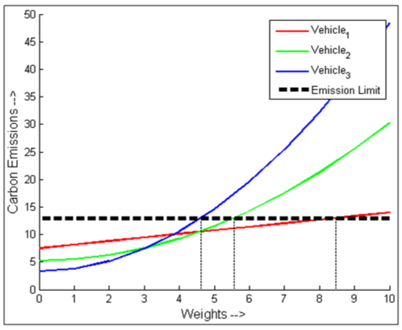
The transportation cost and emission rate for each vehicle vary:

$$
\begin{aligned}
TC\_vehicle_1 &= \lambda_1 + \mu_1 * w_i^{\frac{3}{2}} + \nu_{1*} d_{i0} \\
TC\_vehicle_2 &= \lambda_2 + \mu_2 * w_i^2 + \nu_2 * d_{i0} \\
TC\_vehicle_3 &= \lambda_3 + \mu_3 * w_i^{\frac{5}{2}} + \nu_3 * d_{i0}
\end{aligned} \tag{29}
$$

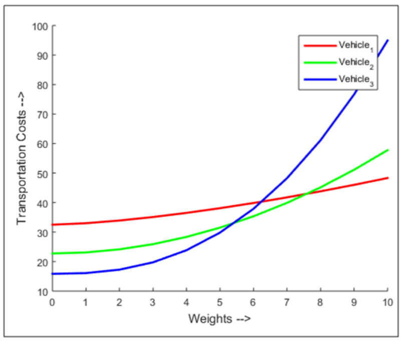
$$
\begin{aligned}
Emission\_vehicle_1 &= \theta_1 + \tau_1 * w_i \\
Emission\_vehicle_2 &= \theta_2 + \tau_2 * w_i^2 \\
Emission\_vehicle_3 &= \theta_3 + \tau_3 * w_i^2
\end{aligned} \tag{30}
$$

In Eqs. 29 and 30, w_i is the weight of the purchase product at the i^{th} market and d_{i0} is the distance from the i^{th} market to the depot; $\lambda_1, \lambda_2, \lambda_3, \mu_1, \mu_2, \mu_3, \nu_1, \nu_2, \nu_3, \theta_1, \theta_2, \theta_3, \tau_1, \tau_2$, and τ_3 are all different roads, vehicles, and management specific parameters.

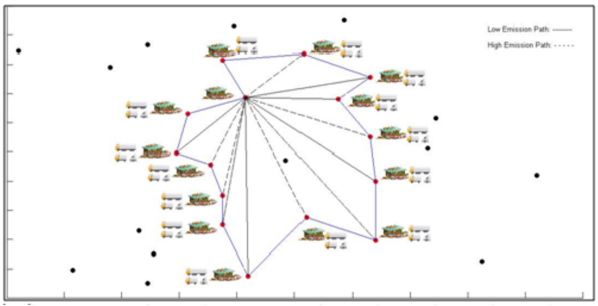
Figure 6(a) plots the emission released by different vehicle types as the vehicle load increases. We show the emission limit threshold and the corresponding load for each vehicle type beyond which a carbon penalty will be incurred. Figure 6(b) presents a similar plot where the emission level is replaced by the total transportation cost. In Figure 6(c), we visually demonstrate the change in market selection and transportation network when the carbon penalty is and is not considered. The dashed and solid lines indicate the transportation networks when the carbon penalty is respectively ignored and included in the total cost calculation.



(a) Emission vs. vehicles with weight



(b) Transportation cost vs. weight



(c) Market planning solid green TPP

Figure 6: Market planning with different vehicles

Parameters with values chosen for numerical experiment

Parameters	Domain Value/Range	Parameters	Domain Value/Range
Number of Chromosomes	50–150	λ_1	7.5
Max_Initialization	100–500	λ_2	5.25
Max_Generation	300–1000	λ_3	3.35
p_c	0.20–0.75	θ_1	5.5
p_m	0.01–0.20	θ_2	3.25
Qubit Initialization Limit	0.51–0.75	θ_3	1.35
Qubit Selection Limit	0.61–0.75	μ_1	0.5
No. of Substitute Items	2	μ_1	0.35
Impact of Self Price (ξ_1)	0.05–0.09	μ_3	0.25
Impact of Substitute Price (ξ_2)	0.05–0.07	τ_1	0.5
α_1	0.75–0.95	τ_2	0.25
α_2	0.75–0.85	τ_3	0.35
α_3	0.5–0.9	s_1	99
γ	0.5	s_2	149
δ	0.5	η	1.75
d_k	10%–90%	μ, ν	0.5

4.2.1. Comparison of classical (Scenario II) and modified (Scenario I) traveling purchaser problem

In this section, we examine the importance of the proposed modification of the classical TPP. In the classical TPP, a purchaser passes through the selected markets and purchases products to convey to the depot. Here, we propose a scenario where the starting depot considers some buffer stock and, after the purchaser reaches the selected market, the purchased products are immediately transported to the depot. The travel and transport cost only and a varied product demand were considered. The results are shown in Table 4. In all cases, we find that, if the emission level is considered, the modified TPPs perform best. We chose a smaller problem size of 10 nodes to examine the implication of the results obtained. The cost of regular and substitute items were fixed as 99 and 149 per item, respectively. With a total market demand of 350 items, we obtained the market availability by choosing a value randomly within a range $[40, 100]$ and $[10, 100]$ for regular and substitute items, respectively.

Table 4: Comparison of classical and modified traveling purchaser problem

Demand	Classical Scenario II	TPP	Modified Scenario I	TPP
	Cost	Emission	Cost	Emission
250	1945	2699.28	1606	2102.45
300	3666	2493.31	2520	2267.81
350	5587	3402.42	4364	1695.79
400	6106	5331.43	5263	1756.82
450	6678	8176.49	7295	1695.49

4.2.2. Two-dimensional imprecise modified solid green traveling purchaser problem in crisp environment

In this section, we summarize the results obtained using iMSGTPP as the problem context by considering both emission and total cost for different vehicle types, route distances, road types, load factors, etc. For both traveling and transportation, we considered three types of vehicles. The traveling cost matrix and distance matrix for a three-dimensional TPP are presented in Tables A1 and A2 (included in the supplementary section), respectively.

Table 5: Results of two-dimensional imprecise modified solid green traveling purchaser problem in crisp environment

Algo.	Path[Travel Vehicle][Transport Vehicle][Purchase Units] Availability =40–100 units in each market	Total Cost	Emission Produced	E_{Max}	Emissions Limit	Carbon Credit	Carbon Penalty	Paid Cost
Q_iGA	3[1][][84]–5[1][1][98]–0[1][1][46]–1[1][1][74]–2[1][1][48]	39110.00	1543.29	1800	1600	56.71	-	39053.29
	0[1][][92]–9[1][1][89]–8[1][1][77]–6[1][1][92]	39095.00	1552.65			47.35	-	39047.65
	0[1][][100]–1[1][1][58]–2[1][1][96]– 5[1][1][96]	39082.50	1683.46			-	83.46	39165.46
	0[1][][82]–4[1][1][86]–2[1][1][96]– 1[1][1][86]	39103.50	1703.55			-	103.55	39207.05
	9[1][][92]–4[1][1][76]–2[1][1][97]–3[1][1][85]	39064.00	1720.59			-	120.59	39184.59
	9[1][][93]–1[1][1][76]–0[1][1][100]–6[1][1][81]	39065.00	1735.74			-	135.74	39200.74
	9[1][][94]–6[1][1][99]–0[1][1][96]–4[1][1][61]	39068.00	1778.33			-	178.33	39246.33

The results are given in Table 5. We considered two emission thresholds: A) E_{max}, the maximum permissible emission level and B) "Emission Limit, that is, the level beyond which a carbon penalty is imposed on the purchase manager. We considered the carbon penalty to be linearly proportional to the excess emission beyond the limit. We also changed the penalty expression associated with carbon emission to observe its impact on key decisions.

First, we solved a two-dimensional MSGTPP problem considering only one vehicle type for traveling and transportation. We solved this problem using Q_iGA; the results are presented in Table 5. We considered the values of the "Emission Limit and E_{max} 1600 and 1800, respectively.

The table highlights some interesting insights. Some route and vehicle combinations may appear very lucrative and hence may be preferred over others, even if they lead to higher emissions. However, after incorporation of the carbon debit (credit), decisions change as the total cost increases (decreases) based on the environmental assessment.

4.2.3. Three-dimensional imprecise modified solid green traveling purchaser problem in crisp environment

We extended the previous problem by introducing multiple (three) vehicle types for traveling and transportation, which were applied separately. The results of three-dimensional MSGTPP (or MSGTPP) under a carbon emission constraint are provided in Table 6. Interestingly, the number of routes selected with a carbon penalty increases with the decreasing availability in each market. This observation adds to the trade-off discussion regarding market expansion (contraction), in terms not only of total cost but also of environmental impact. That the vehicle type changes when the carbon penalty is introduced is also a noteworthy observation. We examined this observation further by observing the change in the emission level and transportation cost with the change in vehicle load, as shown in Figure 6.

Table 6: Results of three-dimensional modified solid green traveling purchaser problem in crisp environment

Algo.	Path[Travel Vehicle][Transport Vehicle][Purchase Units]	Total Cost	Emission Produced	E_{Max}	Emissions Limit	Carbon Credit	Carbon Penalty	Paid Cost
	Product availability 40–100 units in each market							
	9[3][][94]–4[1][1][89]–8[2][1][81]–5[1][1][86]	35133.50	1660.75			39.25	-	35173.25
	4[1][][87]–2[2][1][95]–5[1][1][85]–3[3][1][83]	35140.50	1660.62			39.38	-	35100.05
Q_iGA	0[3][][94]-6[3][1][86]- 7[1][1][79]- 9[2][1][91]	35125.00	1675.96			24.04	-	35165.46
	4[3][][99]–8[3][1][96]–9[1][1][74]–6[3][1][81]	35103.00	1688.04	1800	1700	21.96	-	35207.05
	8[1][][79]–3[3][1][92]–5[2][1][84]–9[1][1][95]	35123.50	1691.75			8.25	-	35184.59
	5[1][][73]–3[2][1][94]–8[2][1][97]–4[1][1][86]	35059.00	1701.25			-	1.25	35060.25
	1[1][][99]–4[2][1][73]–8[1][1][97]–3[3][1][81]	35049.00	1774.34			-	74.34	35135.34
	5[1][][82]–0[1][1][94]–2[2][1][82]–3[2][1][92]	35053.00	1697.89			2.11	-	35050.89
	0[1][][90]–1[3][1][89]–8[3][1][91]–5[2][1][80]	35077.00	1758.44			-	58.34	35135.34
	Product availability 10–100 units in each market							
	0[1][][17]–8[3][1][85]–4[1][1][79]–2[2][1][81]– 6[3][1][88]	35339.00	1687.59			12.41	-	35316.89
Q_iGA	0[3][][100]–4[1][1][73]–2[3][1][93]– 6[2][1][84]	35156.00	1782.28				82.28	35238.28
	3[3][][77]–0[2][1][93]–1[3][1][93]–8[3][3][13]–4[3][3][28]–7[3][3][18]– 5[3][3][28]	35834.40	1997.89	2000	1800	-	297.89	36031.41
	5[3][][25]–1[3][1][94]–4[1][3][21]–6[2][1][97]–2[2][1][98]– 9[2][3][15]	35478.45	1938.42				238.42	35716.89

4.3. Imprecise Modified Solid Green Traveling Purchaser Problem with Substitute Items in Crisp Environment

4.3.1. Two-dimensional imprecise modified solid green traveling purchaser problem with substitute items in crisp environment

In this section, we consider substitute items in two-dimensional iMSGTPP, where multiple items of a single product are purchased. In Table 7, the costs for a single product item and its substitute item are considered to be \$99 and \$149, respectively. Here, we consider the availability to be 40–100 and 10–100 for both items. For the first case, a total demand of 319 units and for the second case of 350 units are considered. In both cases, for travel, only a single vehicle is considered.

Table 7: Results of two-dimensional modified solid green traveling purchaser problem with substitution in crisp environment

Algo	Path[Travel Vehicle][Transport Vehicle][Purchase Units] Product availability 40–100 units in each market	Total Cost	Emission Produced	E_{Max}	Emissions Limit	Carbon Credit	Carbon Penalty	Paid Cost
	0[1][][68 48]–9[1][1][33 40]–3[1][1][33 43]–2[1][3][29 8]–1[1][3][10 0]	42130	1836.20			-	636.20	42766.2
	5[1][][31 48]–3[1][1][33 43]–9[1][1][33 40]–0[1][3][21 15]–7[1][3][39 0]–4[1][3][16 0]	42139	1406.13			-	206.13	42345.13
Q$_i$GA	6[1][][48 41]–9[1][1][33 40]–5[1][1][31 48]–0[1][3][21 17]–1[1][3][40 0]	42152	2393.78			-	1193.78	43345.18
	1[1][][47 49]–9[1][1][33 40]–3[1][1][33 43]–4[1][3][21 14]–8[1][3][39 0]	42153	1314.26			-	114.26	42267.26
	1[1][][47 49]–2[1][2][29 30]–5[1][1][31 48]–0[1][3][21 19]–9[1][3][33 0]–4[1][3][12 0]	42162	2378.39			-	1178.39	43340.39
	Substitute first item=173, second item=146, total unit=319			2400	1200			
						-		
	1[1][][47 49]–9[1][1][33 40]–3[1][1][33 43]–4[1][3][21 14]–0[1][3][21 0]–7[1][3][18 0]	42257	1045.96			154.04	-	42102.96
	1[1][][47 49]–8[1][1][47 32]–5[1][1][31 48]–0[1][3][21 17]–6[1][3][27 0]	42437	1107.24			92.76	-	42344.24
	1[1][][47 49]–8[1][1][47 32]–5[1][1][31 48]–0[1][3][21 17]–9[1][3][27 0]	42359	1108.99			91.01	-	42267.99
	6[1][][48 41]–9[1][1][33 40]–5[1][1][31 48]–0[1][3][21 17]–2[1][3][29 0]–3[1][3][11 0]	42175	1151.51			48.49	-	42126.51
	1[1][][47 49]–9[1][1][33 40]–5[1][1][31 48]–2[1][3][29 9]–3[1][3][33 0]	42239	1191.21			8.79	-	42230.21
	1[1][][47 49]–4[1][2][21 23]–9[1][1][33 40]–3[1][1][33 43]–5[1][3][31 9]–2[1][3][21 0]	46774	2125.72			-	725.72	47499.72
	5[1][][31 48]–3[1][1][33 43]–9[1][1][33 40]–4[1][2][21 23]–2[1][3][29 10]–7[1][3][39 0]	46825	1737.02			-	337.02	47162.02
Q$_i$GA	8[1][][47 32]–5[1][1][31 48]–3[1][1][33 43]–4[1][2][21 23]–0[1][3][21 18]–6[1][3][33 0]	47075	1627.45			-	227.45	47299.45
	7[1][][39 44]–9[1][1][33 40]–5[1][1][31 48]–0[1][2][21 32]–2[1][3][29 0]–4[1][3][21 0]–3[1][3][12 0]	47406	1326.28			73.72	-	47332.28
	Substitute first item=186, second item=164, total unit=350			2400	1400			
	5[1][][31 48]–3[1][1][33 43]–1[1][1][47 49]–8[1][3][28 0]	46940	898.60			501.4	-	46438.6
	1[1][][47 49]–9[1][1][33 40]–3[1][1][33 43]–4[1][2][21 23]–0[1][3][21 9]–7[1][3][31 0]	46892	1382.36			17.64	-	46874.36
	1[1][][47 49]–4[1][2][21 23]–9[1][1][33 40]–3[1][1][33 43]–5[1][3][31 9]–2[1][3][21 0]	46774	2125.72			-	725.72	47499.72
	6[1][][48 41]–9[1][1][33 40]–3[1][1][33 43]–5[1][1][31 40]–0[1][3][21 0]–7[1][3][20 0]	47291	1173.77			226.23	-	47064.77
GA	1[1][][47 49]–3[1][1][33 43]–5[1][1][31 48]–4[1][2][21 23]–2[1][3][29 1]–7[1][3][25 0]	47072	1300.91			99.09	-	46972.91
	1[1][][47 49]–9[1][1][33 40]–3[1][1][33 43]–0[1][2][21 32]–7[1][3][39 0]–8[1][3][13 0]	47213	1314.82	2400	1400	85.18	-	47127.82
	1[1][][47 49]–4[1][2][21 23]–9[1][1][33 40]–3[1][1][33 43]–2[1][3][29 9]–7[1][3][23 0]	46828	2144.11			-	744.11	47572.11

4.3.2. Three-dimensional imprecise modified solid green traveling purchaser problem with substitute items in crisp environment

In this section, we consider the substitute items in three-dimensional iMSGTPP, when multiple items of a single product are to be purchased. In Table 8, the costs for a single product and its substitute item are considered to be \$99 and \$149, respectively. Here, we consider the availability values to be from 40 to 100 and from 10 to 100 for both items. For the first case, a total demand of 319 units and in the second case a total demand of 350 units are considered. In both cases, three vehicles are considered.

Table 8: Results of three-dimensional modified solid green traveling purchaser problem with substitution in crisp environment

Algo	Path[Travel Vehicle][Transport Vehicle][Purchase Units] Product availability 40–100 units in each market	Total Cost	Emission Produced	E_{Max}	Emissions Limit	Carbon Credit	Carbon Penalty	Paid Cost
	7[2][][39 44]–9[3][1][33 40]–4[2][2][21 23]–3[1][3][33 5]–8[3][3][0 32]	41369	1215.08			-	15.08	41384.08
	1[3][][47 49]–9[3][1][33 40]–3[2][1][33 43]–0[1][3][21 14]–7[2][3][39 0]	42057	1305.61			-	105.61	42162.16
Q$_i$GA	1[3][][47 49]–9[2][1][33 40]–3[3][1][33 43]–0[1][3][21 14]–7[3][3][39 0]	42054	1305.61			-	105.61	42159.61
	1[3][][47 49]–9[1][1][33 40]–3[3][1][33 43]–0[2][3][21 14]–7[3][3][39 0]	42117	1305.61			-	105.61	42222.61
	1[3][][47 49]–9[3][1][33 40]–3[3][1][33 43]–4[3][3][21 14]–6[3][3][39 0]	41991	1310.51			-	110.51	42101.51
	Substitute first item=173, second item=146, total unit=319			2500	1200			
	1[3][][47 49]–3[1][1][33 43]–9[1][1][33 40]–4[1][3][21 14]–6[1][3][39 0]	42021	2422.18			-	1222.18	43243.18
	1[3][][47 49]–9[3][1][33 40]–3[2][1][33 43]–0[3][3][21 14]–6[1][3][39 0]	42024	1310.66			-	110.66	42134.66
Q$_i$GA	6[1][][48 41]–9[3][1][33 40]–5[1][1][31 48]–0[2][3][21 17]–1[2][3][40 0]	42407	1278.05			-	78.05	42485.05
	1[1][][47 49]–8[1][1][47 32]–5[1][1][31 48]–0[1][3][21 17]–6[1][3][27 0]	42437	1107.24			92.76	-	42644.24
	1[1][][47 49]–3[1][1][33 43]–4[1][2][21 23]–2[3][2][29 30]–0[3][3][21 19]–8[2][3][35 0]	46732	3324			-	1924	48656
	6[1][][48 41]–9[1][1][33 40]–5[1][1][31 48]–4[3][2][21 23]–0[1][3][21 12]–7[1][3][32 0]	46900	1484.51			-	84.51	46984.51
	1[3][][47 49]–9[1][1][33 40]–5[1][1][31 48]–0[1][2][21 27]–4[3][3][21 0]–6[3][3][33 0]	46955	1357.44			42.56	-	46912.44
	Substitute first item=186, second item=164, total unit=350			2500	1400			
	6[1][][48 41]–7[2][1][39 44]–4[1][2][21 23]–8[2][2][31 24]	46658	1306.06			93.94	-	46564.06
	1[3][][47 49]–9[1][1][33 40]–3[1][1][33 43]–4[3][2][21 23]–0[1][3][21 9]–6[2][3][31 0]	46605	1387.41			12.59	-	46593.41
	5[3][][31 48]–3[2][1][33 43]–8[3][1][47 32]–4[3][2][21 23]–0[2][3][21 18]–9[1][3][33 0]	46574	1623.43			-	223.43	46797.43
	1[3][][47 49]–5[2][1][31 48]–4[1][2][21 23]–9[2][1][33 40]–3[1][3][33 4]–6[3][3][21 0]	46516	2133.62				733.62	47249.62
	5[1][][31 48]–3[2][1][33 43]–4[3][2][21 23]–9[1][1][33 40]–2[2][3][29 10]–8[3][3][39 0]	46842	2498.61			-	1098.61	47940.61
GA	1[3][][47 49]–9[1][1][33 40]–4[3][2][21 23]–5[3][1][31 48]–3[3][3][33 4]–0[3][3][21 0]	46968	2319.77	2500	1400	-	919.77	47887.77
	7[1][][39 44]–9[3][1][33 40]–5[1][1][31 48]–0[1][2][21 32]–3[1][3][33 0]–1[3][3][29 0]	47718	2493.69			-	1093.69	48811.69

We conclude this section by presenting the results of the iMSGTPP with substitutable items with a single vehicle type (Table 7) and with multiple vehicle types (Table 8). The cost of the main product and substitute are varied as $99 and $149, respectively.

4.4. Imprecise Modified Solid Green Traveling Purchaser Problem in Fuzzy Environment

4.4.1. Three-dimensional imprecise modified solid green traveling purchaser problem in fuzzy environment

Here, we took the travel and transportation cost as fuzzy values with TFN. The uncertain fuzzy traveling and transportation cost matrices for this iMSGTPP model are provided in the online supplement for interested readers. In our experiments, we followed the possibility, necessity, and credibility approaches. The problem size remained at 10 market nodes with an aggregate demand of 350 units. The results under a fuzzy environment are reported in Table 9 for different confidence levels. We also ran a traditional GA and report the results to compare the solution quality.

Table 9: Results of three-dimensional imprecise modified solid green traveling purchaser problem in fuzzy environment without substitution

Algo	α_1	α_2	Algo.	DM DM	Path[Travel Vehicle][Transport Vehicle][Purchase Units] Availability 40–100	Obj Value	Emission Produced	E_{Max}	Emissions Limit	Carbon Credit	Carbon Penalty	Paid Cost
				ODM	8[2][][94]–5[3][1][73]–0[3][1][72]–2[1][2][49]–6[1][3][40]–7[2][3][22]	38548.1	1393.42			6.58	-	38541.52
				PDM	8[2][][94]–5[3][1][73]–0[3][1][72]–2[1][2][49]–6[1][3][40]–7[2][3][22]	38561.21	1393.42				-	38554.63
Pos.	0.95	0.8	Q_iGA	ODM	7[1][][94]–0[2][1][72]–5[2][1][73]–3[3][2][56]–6[1][3][40]–9[3][3][13]	38763.86	1328.68			71.32	-	38692.54
				PDM	7[1][][96]–0[2][1][72]–5[2][1][73]–3[3][2][56]–6[1][3][40]–9[3][3][13]	38773.33	1328.68					38702.01
				ODM	9[2][][100]–8[1][1][94]–0[1][1][72]–2[1][2][49]–7[2][3][35]	39349.36	1271.00			129	-	39220.36
				PDM	9[2][][100]–8[1][1][94]–0[1][1][72]–2[1][2][49]–7[2][3][35]	39356.72	1271.00					39227.72
Nes.			GA	ODM	7[1][][96]–0[1][1][72]–4[3][2][69]–2[3][2][49]–6[2][3][40]–3[1][3][24]	38919.49	1829.99			-	429.99	39349.48
				PDM	7[1][][96]–0[1][1][72]–4[3][2][69]–2[3][2][49]–6[2][3][40]–3[1][3][24]	38930.82	1829.99					38820.81
				ODM	8[2][][94]–5[3][1][73]–0[3][1][72]–2[1][2][49]–6[1][3][40]–7[2][3][22]	38527.42	1393.42			6.58	-	38520.84
				PDM	8[2][][94]–5[3][1][73]–0[3][1][72]–2[1][2][49]–6[1][3][40]–7[2][3][22]	38558.31	1393.42					38551.73
	.8	.95	Q_iGA	ODM	7[1][][96]–8[1][1][94]–5[3][1][73]–2[2][2][49]–9[3][3][38]	39388.35	1332.87	2500	1400	67.13	-	39321.22
				PDM	7[1][][96]–8[1][1][94]–5[3][1][73]–2[2][2][49]–9[3][3][38]	39397.52	1332.87					39330.39
			GA	ODM	7[1][][96]–8[1][1][94]–0[1][1][72]–2[3][2][49]–6[2][3][39]	39336.38	1343.43			56.57	-	39279.81
				PDM	7[1][][96]–8[1][1][94]–0[1][1][72]–2[3][2][49]–6[2][3][39]	39344.81	1343.43					39278.24
	α_3											
Credi		-		-	7[1][][96]–0[2][1][72]–5[2][1][73]–3[3][2][56]–6[1][3][40]–9[3][3][13]	38768.61	1328.68			71.32	-	38697.29
bility	0.6	-		-	9[1][][100]–8[1][1][94]–0[1][1][72]–2[2][2][49]–1[2][3][35]	39312.53	1269.70			130.3		39182.23
		-	Q_iGA	-	9[2][][100]–8[1][1][94]–0[1][1][72]-2[1][2][49]–7[2][3][35]	39353.04	1271.00			129	-	39224.04
		-		-	9[1][][100]–8[2][1][94]–5[3][1][73]–0[2][1][72]–1[2][3][11]	39780.56	1123.94			276.06	-	39504.5
		-		-	7[1][][96]–8[1][1][94]–0[1][1][72]–2[3][2][49]–6[2][3][39]	39340.6	1343.43			56.57	-	39284.03
		-	GA	-	7[1][][96]–8[1][1][94]–5[3][1][73]–2[2][2][49]–9[3][3][38]	39392.94	1332.87			67.13	-	39325.81
		-		-	7[1][][96]–5[3][1][73]–0[1][1][72]–4[3][2][69]–6[1][3][40]	39298.02	1334.73			65.27	-	39232.75
		-		-	7[2][][96]–8[3][1][94]–5[2][1][73]–2[3][2][49]–4[1][3][38]	39426.81	1327.78			72.22	-	39354.59
	0.5	-	Q_iGA	-	9[1][][100]–8[2][1][94]–0[1][1][72]–2[3][2][49]–5[1][3][35]	39321.97	1274.26			125.74	-	39196.23
		-		-	9[2][][100]–0[2][1][72]–7[2][1][96]–2[3][2][49]–5[3][3][33]	39449.33	1252.08			147.92	-	39301.41

4.4.2. Three-dimensional imprecise modified solid green traveling purchaser problem with substitute in fuzzy environment

This section extends the results obtained by including substitute items. The results are presented in Table 10.

Table 10: Results of three-dimensional imprecise modified solid green traveling purchaser problem with substitution in fuzzy environment

Algo	α_1	α_2	Algo.	DM DM	Path[Travel Vehicle][Transport Vehicle][Purchase Units] Availability 40–100	Obj Value	Emission Produced	E_{Max}	Emissions Limit	Carbon Credit	Carbon Penalty	Paid Cost
				ODM	1[2][][47 49]–3[1][1][33 43]–9[1][1][33 40]–4[2][2][21 23]–2[2][3][29 9]–5[3][3][23 0]	46751.77	1370.58			29.42	-	46722.35
				PDM	1[2][][47 49]–3[1][1][33 43]–9[1][1][33 40]–4[2][2][21 23]–2[2][3][29 9]–5[3][3][23 0]	46765.93	1370.58					46736.51
Pos.	0.95	0.8	Q_iGA	ODM	1[3][][47 49]–3[1][1][33 43]–5[2][1][31 48]–8[3][1][47 24]–6[3][3][28 0]	47503.61	1090.26			309.74	-	47193.87
				PDM	1[3][][47 49]–3[1][1][33 43]–5[2][1][31 48]–8[3][1][47 24]–6[3][3][28 0]	47510.3	1090.26					47200.56
POS.				ODM	6[1][][48 41]–7[3][1][39 44]–9[2][1][33 40]–3[1][1][33 39]– 5[3][3][31 0]–8[1][3][2 0]	47502.73	1121.25			278.25	-	47223.98
				PDM	6[1][][48 41]–7[3][1][39 44]–9[2][1][33 40]–3[1][1][33 39]– 5[3][3][31 0]–8[1][3][2 0]	47581.44	1121.25					47303.19
NES.			GA	ODM	6[3][][48 41]–9[1][1][33 40]–5[2][1][31 48]–4[2][2][21 23]–0[1][3][21 12]–1[2][3][32 0]	46865.52	1483.01			-	83.01	46948.53
				PDM	6[3][][48 41]–9[1][1][33 40]–5[2][1][31 48]–4[2][2][21 23]–0[1][3][21 12]–1[2][3][32 0]	46872.42	1483.01					46955.43
				ODM	1[2][][47 49]–9[3][1][33 40]–5[3][1][31 48]–0[1][2][21 27]–4[2][3][21 0]–8[1][3][33 0	46949.5	1361.19			38.81	-	46910.69
				PDM	1[2][][47 49]–9[3][1][33 40]–5[3][1][31 48]–0[1][2][21 27]–4[2][3][21 0]–8[1][3][33 0]	46959.26	1361.19					46920.45
				ODM	1[1][][47 49]–9[2][1][33 40]–3[2][1][33 43]–2[3][2][29 30]–5[1][3][31 2]–0[1][3][13 0]	47165.52	1236.28			163.72	-	47001. 8
				PDM	1[1][][47 49]–9[2][1][33 40]–3[2][1][33 43]–2[3][2][29 30]–5[1][3][31 2]–0[1][3][13 0]	47176.77	1236.28					47013.05
	.8	.95	Q_iGA	ODM	1[1][][47 49]–9[2][1][33 40]–3[2][1][33 43]–2[1][2][29 30]–5[3][3][31 2]–0[1][3][13 0]	47213.44	1236.28	2500	1400	163.72	-	47049.72
				PDM	1[1][][47 49]–9[2][1][33 40]–3[2][1][33 43]–2[1][2][29 30]–5[3][3][31 2]–0[1][3][13 0]	47226.54	1236.28					47062.82
			GA	ODM	5[2][][31 48]–3[3][1][33 43]–7[3][1][39 44]–2[2][2][29 29]–0[3][3][21 0]–1[3][3][33 0]	47664.45	1455.30			-	55.3	47719.75
				PDM	5[2][][31 48]–3[3][1][33 43]–7[3][1][39 44]–2[2][2][29 29]–0[3][3][21 0]–1[3][3][33 0]	47677.14	1455.30					47732.44
	α_3											
Credi	0.6	-		-	1[1][][47 49]–7[1][1][39 44]–9[2][1][33 40]–0[3][2][21 31]–4[2][3][21 0]–8[1][3][25 0]	47256.36	1245.9			154.1	-	47102.26
bility		-	Q_iGA	-	1[2][][47 49]–3[1][1][33 43]–5[1][1][31 48]–2[2][2][29 24]–9[3][3][33 0]–4[3][3][13 0]	47262.8	1241.51			158.49	-	47104.31
		-		-	1[1][][47 49]–9[3][1][33 40]–3[1][1][33 43]- 2[1][2][29 30]–4[1][3][21 2]–8[3][3][23 0]	47160.05	1227.90			172.1	-	46987.95
		-	GA	-	1[2][][47 49]–9[3][1][33 40]–0[1][2][21 48]–2[1][2][29 27]–5[2][3][31 0]–3[2][3][25 0]	47360.93	1875.96			-	475.96	47836.89
		-		-	1[2][][47 49]–3[1][1][33 43]–9[1][1][33 40]–4[2][2][21 23]–2[2][3][29 9]–5[3][3][23 0]	46758.84	1370.58			29.42	-	46729.42
	0.5	-	Q_iGA	-	1[3][][47 49]–8[1][1][47 32]–7[3][1][39 44]–4[2][2][21 23]– 0[2][3][21 16]–3[3][3][11 0]	47213.17	1295.04			104.96	-	47108.21
		-		-	6[1][][48 41]–9[1][1][33 40]–3[2][1][33 43]–5[1][1][31 40]–0[3][3][21 0]–4[1][3][20 0]	47229.96	1171.27			228.73	-	47001.23
		-	GA	-	1[1][][47 49]–3[1][1][33 43]–0[3][2][21 48]–4[2][2][21 23]–9[2][3][33 1]–5[3][3][31 0]	47063.89	1761.21			-	361.21	47425.1

4.5. Statistical Test

A statistical test, analysis of variance (ANOVA), was performed. We used benchmarks instances from Table 3 with a 40–100 availability value considering the optimal values. To judge efficiency, we chose three algorithms: Q_iGA, simple GA (SGA) (roulette wheel (RW) selection, cyclic crossover), and a modified GA (MGA) (probabilistic selection, comparison crossover) proposed by Maity et al. (2015). In Table 11, we present the number of achievements in 100 individual runs for the given benchmark instances using the algorithms Q_iGA, SGA, and MGA, respectively.

Table 11: Number of wins for different algorithms

Problem	bayg29	korA100	korB100	korC100	korD100	korE100	korA150	korB150	korA200	korB200	p654
Q_iGA	92	89	86	69	84	79	88	91	84	85	83
SGA	59	71	48	51	58	46	62	56	53	65	45
MGA	72	82	59	76	64	71	65	66	65	62	72

To reduce the calculation complexity of the ANOVA, we subtracted 55 (without loss of generality) from each number and thus Table 11 is reduced to Table 12.

Table 12: Table reduced from Table 11

Problem	bayg29	korA100	korB100	korC100	korD100	korE100	korA150	korB150	korA200	korB200	p654	Mean
X_1	37	34	31	14	29	24	33	36	29	30	28	$\overline{X}_1$=29.54
X_2	4	16	-7	-4	3	-9	7	1	-2	10	-10	$\overline{X}_2$=0.81
X_3	17	27	4	21	9	16	10	11	10	7	17	$\overline{X}_3$=13.55

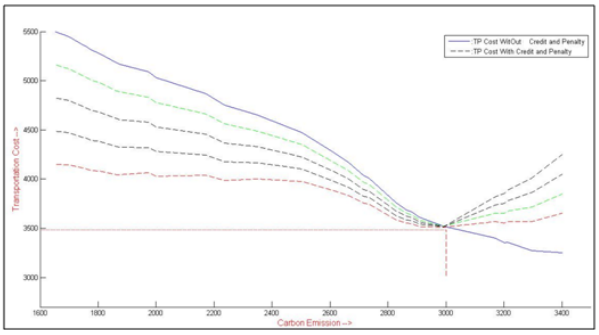
The number of benchmark instances (I=11) was equal for each algorithm (J=3). The mean of the sample means $\overline{\overline{X}}$=14.63

Table 13: Analysis of variance summary (data taken from Table 12)

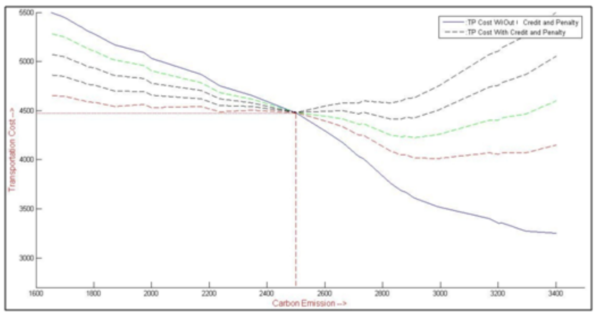
Source of variation	Sum of square	df	Mean of square	F
Between groups	SS_B=4559.17	J-1=2	$MS_B=\frac{SS_B}{J-1}$=2279.58	
Within groups	SS_W=1361.3	J(I-1)=30	$MS_W=\frac{SS_W}{J(I-1)}$=45.37	$\frac{MS_B}{MS_W}$=50.24
Total	SS_T=5920.47	IJ-1=32		

The critical values of F is $F_{0.05(2,30)} \approx 3.32$. As the computed F (in Table 13) is higher (38.36) than the critical F value (3.32) for 0.05 level of significance, it could be concluded that a noteworthy contrast exists between the groups. When the F ratio is found to be significant in an ANOVA with more than two groups, it should be followed by multiple comparison tests to determine which group means differ significantly from each other. Therefore, Scheffe's multiple comparison F-test was conducted to determine whether the results of Q_iGA and SGA and/or Q_iGA and MGA differ. For the first pair, i.e., Q_iGA and MGA, the calculated F value is obtained by $F=\frac{(\overline{X}_1-\overline{X}_3)^2}{MS_W(\frac{1}{I}+\frac{1}{J})}$=13.34. Similarly, for the second pair, i.e., Q_iGA and SGA, the calculated F value is 42.9. As both calculated F values are greater than the tabulated value (3.32), there is a significant difference between Q_iGA and SGA and also between Q_iGA and MGA. In Table 12, it can be observed that the mean $(\overline{X}_1)$ of X_1 is higher than the other two means, $\overline{X}_2$ and $\overline{X}_3$. Significant differences between the algorithms are observed, and therefore, it can be concluded that Q_iGA outperforms the other two algorithms.

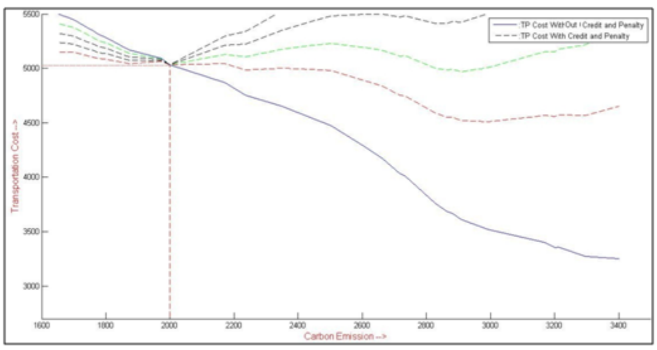
4.6. Managerial Insights



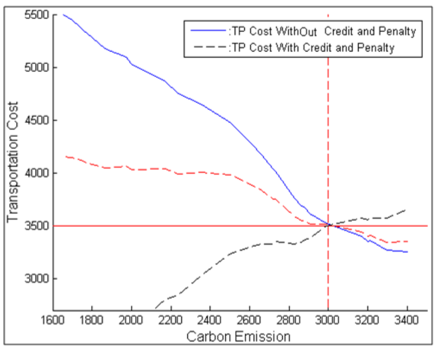
(a) Emission vs. transportation cost



(b) Emission vs. transportation cost



(c) Emission vs. transportation cost



(d) Emission vs. transportation cost

Figure 7: Emission vs. transportation cost scenario

Figure 7 shows the details of the changes in transportation cost when the emission penalty is included for different values of E_{max}. We did not consider an item's substitutability in these graphs (refer Table 6). Figures 7(a) to 7(c) show the impact with varying threshold values of "Emission Limit and E_{max} set at 3500. We present our interpretation in Figure 7(a) with the "Emission Limit value set at 3000. The case for Figures 7(b) and 7(c) would be similar. In Figure 7(a), the solid line represents the trend of the total cost when a carbon credit/debit is not considered. The dashed lines indicate the revised transportation cost if the carbon credit or debit is adjusted suitably based on whether the emission level is below or above the limit. The variation in the dashed lines emphasizes the trends when the per unit credit/debit values are adjusted. It can be easily observed from the solid line representing the costs with the carbon emissions credit and penalty that transportation costs are reduced as the limits on carbon emissions increase. We observe that the adjusted costs become lower (higher) than the actual costs if the actual emissions are lower (higher) than the limit and hence the carbon credit (debit) is adjusted in the total cost. As emission limits become strict, the introduction of a carbon penalty or subsidy incentivizes the purchase manager to select routes that involve lower emissions. Figure 7(d) captures the change in transportation cost for very high and low penalty values. In summary, Figure 7 can help policy makers decide the appropriate levels of emission limits and their impact, whereas purchase managers can utilize this information to determine the appropriate level of emission to minimize the adjusted transportation cost subject to the constraints.

5. Conclusion

In this study, we conducted a two-fold investigation, the formulation of a realistic TPP model and the development of a fast and reliable solution methodology.

The classical TPP was rendered more realistic by introducing the following features. Different types of vehicles are available at market locations for the travel of the purchaser and transportation of the goods (STPP). Two alternatives for transporting the goods to the depot, i.e., transportation from the market to the depot directly or transportation in the same vehicle as the purchaser for the entire route, are considered, and the better alternative is selected. The vehicles used for travel and transport emit GHG, which is proportional to the total weight of the goods and types of vehicles together with the distance traveled. The cost of emissions depends on the government subsidy and the penalty incurred for exceeding the limit. So that it will be more realistic, the costs in this model are uncertain and are introduced as fuzzy numbers. Instead of a single item, two substitute items, substituted against their prices, are considered. Ultimately, the appropriate markets for the purchaser, appropriate route from each market, and the better alternative for transporting the goods to the depot are selected. The total costs for both the travel of the purchaser and the transportation of goods are minimized, subject to the carbon emission constraint.

Taking quantum behavior into consideration to achieve a methodological improvement, in this study a quantum-inspired GA algorithm with an IVF crossover technique and sigmoid mutation was developed to solve the above NP-hard problems. The developed Q_iGA was tested statistically using problems from the TSPLIB repository. Several variations of the problem formulated above were formulated and solved. All the results were compared.

This investigation was directly related to real-life purchasing and distribution problems that are valid for sourcing organizations, such as vendors and retail shop owners. Its results can be used in other optimization applications, such as network optimization, graph theory, solid transportation problems, production planning, vehicle routing, and very large scale integration

(VLSI) chip design. With minor customization, in our opinion the presented Q_iGA will achieve similar success in other combinatorial optimization problems. We clearly established its dominance over traditional GAs in terms of solution quality and computation time. Although we attempted to include certain practical complexities in this model, we could not accommodate them all and the rest remain as limitations that can be studied further. For example, in our study we considered the case where all the purchases are transported to one central depot. It might be interesting to extend this problem to a multi-depot problem. In our model, we focused primarily on travel and transportation costs and hence we did not consider purchase costs and thus we made them uniform across markets. In practice, purchase managers attempt to exploit the arbitrage opportunity provided by differential purchase prices across markets.

Appendix A.

Appendix A.1. Fuzzy Possibility and Necessity Approach

Consider $\tilde{a}$ and $\tilde{b}$ to be fuzzy numbers with given membership functions $\mu_{\tilde{a}}(x)$ and $\mu_{\tilde{b}}(x)$, respectively. According to Dubois and Prade [15]

$$pos(\tilde{a} * \tilde{b}) = sup\{min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y)), x, y \in \Re, x * y\} \tag{31}$$

Here, *pos* stands for possibility, $*$ stands for any relations $>, <, =, \leq, \geq$, and $\Re$ is the set of real numbers.

$$nes(\tilde{a} * \tilde{b}) = 1 - pos\overline{(\tilde{a} * \tilde{b})} \tag{32}$$

Here, *nes* stands for necessity.
If $\tilde{a}$, $\tilde{b} \subseteq \Re$ and $\tilde{c} = f(\tilde{a}, \tilde{b})$, where $f : \Re \times \Re \to \Re$ is a binary operation, the membership function $\mu_{\tilde{c}}$ of $\tilde{c}$ is defined as

$$\text{For each } z \in \Re, \ \ \mu_{\tilde{c}}(z) = sup\{min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y)), x, y \in \Re \text{ and } z = f(x, y)\} \tag{33}$$

Triangular Fuzzy Number (TFN):

A TFN $\tilde{a} = (a_1, a_2, a_3)$ has three parameters a_1, a_2, and a_3, where $a_1 < a_2 < a_3$ and is given by the membership function $\mu_{\tilde{a}}$, obtained by

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-a_1}{a_2-a_1} & \text{for } a_1 \leq x \leq a_2 \\ \frac{a_3-x}{a_3-a_2} & \text{for } a_2 \leq x \leq a_3 \\ 0 & \text{otherwise.} \end{cases} \tag{34}$$

From the above definitions, the following lemmas can be derived.

Lemma 2.1.a: If $\tilde{a} = (a_1, a_2, a_3)$ is a TFN with $0 < a_1$ and b is a crisp number, then
$pos(\tilde{a} < b) \geq \alpha_1$ iff $\dfrac{b - a_1}{a_2 - a_1} \geq \alpha_1$.

Lemma 2.1.b: If $\tilde{a} = (a_1, a_2, a_3)$ is a TFN with $0 < a_1$ and b is a crisp number, then
$nec(\tilde{a} < b) \geq \alpha_1$ iff $\dfrac{a_3 - b}{a_3 - a_2} \leq 1 - \alpha_1$.

Appendix A.2. Credibility Measure of Fuzzy Number

If $\tilde{a}$, $\tilde{b} \subseteq \Re$ and $\tilde{c} = f(\tilde{a}, \tilde{b})$, where $f : \Re \times \Re \to \Re$ is a binary operation, the membership function is defined by Eq. (3), and the credibility measure of two fuzzy numbers $\tilde{a}$ and $\tilde{b}$ is defined as

$\text{Cr}(\tilde{a} * \tilde{b})= \frac{1}{2}(\text{pos }(\tilde{a} * \tilde{b})+\text{nes }(\tilde{a} * \tilde{b}))$

Credibility satisfies the following conditions.

(i) $\text{Cr}(\phi)=0$, $\text{Cr}(\Re)=1$.

(ii) $\text{Cr}(\tilde{A}) \leq \text{Cr}(\tilde{B})$ whenever $\tilde{A} \subset \tilde{B}$.

(iii) $\text{Cr}(\tilde{A} \leq \alpha_2) \leq \text{Cr}(\tilde{B} \leq \alpha_2)$ whenever $\tilde{A} \subset \tilde{B}$ and α_2 is a given a predetermined value.

Now, for the TFNs $\tilde{A} = (a_1, a_2, a_3)$, the credibility measure $(\tilde{A} \leq x)$, according to Dubosis and Prade (1997), is

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & x \leq a_1 \\ \frac{x-a_1}{2(a_2-a_1)} & a_1 \leq x \leq a_2 \\ \frac{x-2a_2+a_3}{2(a_3-a_2)} & a_2 \leq x \leq a_3 \\ 1 & \text{otherwise.} \end{cases} \tag{35}$$

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