Indian Institute of Management Calcutta
Working Paper Series
WPS No 819 /December, 2018

A multi- (depot, path, vehicle) 4D traveling purchaser problem for perishable and breakable items under disruption through quantum-inspired memetic algorithm

Samir Maity*
Post Doctoral Research Fellow
Operations Management Group
Indian Institute of Management Calcutta
D. H. Road, Joka, Kolkata-700104, India
E-mail: samirm@iimcal.ac.in
(* Corresponding Author)

Kunal Pradhan
Research Assistant
Operations Management Group
Indian Institute of Management Calcutta
D. H. Road, Joka, Kolkata-700104, India
E-mail: kunalpradha86@gmail.com

Bodhibrata Nag
Professor
Operations Management Group
Indian Institute of Management Calcutta
D. H. Road, Joka, Kolkata-700104, India
E-mail: bnag@iimcal.ac.in

Sumanta Basu
Associate Professor
Operations Management Group
Indian Institute of Management Calcutta
D. H. Road, Joka, Kolkata-700104, India
E-mail: sumanta@iimcal.ac.in

Manoranjan Maiti
Former Professor
Dept. Applied Mathematics with Oceanology and Computer Programming
Vidyasagar University, Midanapur-721102, India
E-mail: mmaiti2005@yahoo.co.in

Indian Institute of Management Calcutta
Joka, D.H. Road, Kolkata-700104
URL: http://facultylive.iimcal.ac.in/workingpapers

A multi- (depot, path, vehicle) 4D traveling purchaser problem for perishable and breakable items under disruption through quantum-inspired memetic algorithm

Abstract

The aim of this investigation is on improving the dynamic procurement planning and transporting with selecting appropriate depot. This paper attempts to address decision problems faced by the stakeholders, i.e., retail chains, e-commerce industries for perishable and breakable items with multiple outlets under disruption risk of the path considering different vehicle types for traveling and transportation. Introducing multiple path and vehicles between two markets with considering multiple-depot is making classical traveling purchaser problem (TPP) a multi-depot 4DTPP. Multi-depot 4D (four-dimensional) Traveling Purchaser Problem is a TPP in which, market selection and routing decisions are made by traveling multiple paths and each path having multiple vehicles to minimize traveling, purchasing and transportation costs with multi-depot considering quality of the product and risks factor of the road, vehicles, etc. Again in the variation of product type, we study perishable and breakable items only. This is an NP hard problem, and hence we develop a quantum-inspired memetic algorithm with a novel selection and crossover technique to address this problem. We establish the superiority of our algorithm in terms of solution quality and computational time on benchmark problems. Focusing on issues relevant for practitioners, we address strategic decisions like introducing quality and quantity based policy and appropriate choosing of the transporting vehicles, capacity and its impact on selection of markets and conveyance types, optimal routing and procurement plan etc. In our analysis, we provide a dynamic decision-making framework to regulators for fixing placing depot/warehouse and for designing a route structure to motivate purchasers to opt for high quality with low risky network design.

Keywords: `Traveling Purchaser Problem, Quantum-inspired memetic Algorithm, Perishability, 4D TPP, IVF Crossover;`

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 [51]]. 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. It is an NP-hard discrete optimization problem according to Lawler et al. [31]. TPP as a problem context has become increasingly relevant because it combines market/supplier selection, appropriate path arrangement and, product procurement design to avoid sub-optimality of independently solving each optimization problem. Increasing information access, real time tracking and coordination of various departments facilitate the implementation of TPP.

After allowing 100% foreign direct investment for food retail in India there have stiff competition of supermarket chain with online e-commerce industries "Global retailers, including Amazon, Wal-Mart and Metro AG, are keen to increase their footprint in India to cash in on the consumption growth story of the worlds second populous nation"[cf. Hindustantimes [28]]. Recently, "Amazon has pledged to spend $\cdots$ proposed 500 million entry into the food sector, is ramping up its Amazon Pantry and Amazon Now initiatives" [cf. Times [64]] to expand Amazon business strategy.

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 [40]]. Currently, even in countries such as India and Sri Lanka, international retail houses, such as "Metro Cash and Carry" and "Amazon", do have large warehouses equipped with a food preservation facility and their purchases of several perishable and breakable items from remote markets, such as apple and orange, etc. and different varieties of breakable items such as cashew, biscuits, snacks, etc. with breakable come perishable products such as egg, sweets, etc. in large amounts. They tend to avoid a large number of orders from remotely located sources for the large ordering cost and inconveniences involved, such as the unavailability of an 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 [53]]. 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.

In supermarkets chain have multiple retail stores in a mega city, but they purchase from the different buyer/supplier for different items and sent it into their different retail stores. Take this scenario into account considering the proposed model with suitable multiple depots in the place of a single depot in classical TPP. Thus we called it multi-depot TPP. According to a present situation that at each markets considering appropriate vehicles for procurement manager traveling and also different vehicles for transporting the goods into the depot. Thus the model termed as multi-depot 3D (market-multi vehicle-market) TPP. But it is found that between each market there more than one path(route) available for traveling as well as transporting the goods to the depots also. Accounting this practical observation, we formulate the model and termed as multi-depot 4D (market-multi path-multi vehicle-market) TPP.

Perishable product logistic is a complicated problem for a procurement manager because to find out the best decision designing/ taken at the time of purchasing. It found that more than 40% of foods is wasted in each year at the United States which in the cost of \$218 billion according to Thomson [63]. Again at European Union expected food waste increase to 126 million tons by 2020 as reported by Gutierrez et al. [24]. In the present investigation, we account the perishability of the products which depend on initial product quality, transporting vehicles and road condition with distance covered by the vehicles also.

In our paper, we introduce a novel application of memetic algorithm (MA), Quantum-inspired MA (Q_iMA) to solve proposed $multi-depot\ 4DTPP$. Quantum-inspired MA uses the concept from both quantum computation and Genetic Algorithm (GA) and has successful applications in TSP. Few attempts were done by the researcher for quantum-inspired GA to solve NP-hard like as TSP, TPP, etc. As a methodological contribution, firstly we develop a Quantum-inspired MA (Q_iMA) implementation technique using quantum inspired initialization, selection, and crossover that have not been attempted before. It yields better solution quality than traditional GA in less computational time. In our knowledge there had only a few attempts Narayanan and Moore [45], Talbi et al. [61] are taken in this Quantum-inspired GA for TSP. At the present work we first-time Q_iMA used for TPP also. The novelty of the developed algorithm that superposition dependent initialization and selection operation did in proposed Q_iMA. It facilitates the reduction of computational time without compromising solution quality. We also develop a novel three parents crossover technique (Intro Vitro Fertilization (IVF) crossover) that increases the diversity of the chromosomes obtained after crossover. In mutation, we create a generation dependent sigmoid random mutation probability threshold to influence mutation as the generation progresses. The developed algorithm is compared with benchmarks from (TSPLIB, [52]) against the traditional GA which is the alliance of roulette wheel selection (RW), cyclic crossover with conventional mutation to establish the productivity of the developed algorithm.

This paper contributes to the problem context and methodology in three ways: A) addressing more complex and relevant version of the problem context (TPP), B) methodological contribution by developing a novel quantum-inspired MA-based technique and C) developing policy level insights required for robust decision support systems.

In this paper, we consider a multi-depot, multi-paths TPP with perishable and breakable items having multiple vehicles of different types at marketplaces for travel and transportation. Goods transportation vehicles differ in their costs per unit distance, per unit load, capacities for carrying articles and perishability and breakability depends on the initial quality of the purchase items, road conditions, vehicle capacity, and conditions, distance from the depot, etc. Different types of path and vehicles are used for purchaser's travel and goods transportation. The purchased articles are transported to the depot directly just after the purchase. The purchaser comes back the depot once the demands of the items are fulfilled. This model is termed as multi-depot 4D traveling purchaser problem ($multi-depot\ 4DTPP$) because of additional dimension introduced by multiple depots, paths and vehicles. The problem is to find the suitable routes for the purchaser to purchase and return, to determine the amounts of purchased items from the markets and to send the purchased units to depot under the constraint of perishable and breakability so that sum total of travel and materials' transportation costs is minimum. As these models are NP-hard problems, a Quantum-inspired memetic algorithm (Q_iMA) developed and used for solutions of the above-formulated problems. Solutions of different formulated models are compared. Some managerial decisions are also derived.

Thus main contributions in this investigation are as follows:

- Making a general TPP as multi-depot and introducing different types of paths and vehicles at each market for travelling as well as transportation
- Procurement of perishable and breakable items from the markets against their demands at the depot influenced by their prices or quality
- Breakability and perishability of the product depends on the road condition as well as vehicles specific parameters
- Development of a novel Quantum-inspire memetic algorithm.
- Imposition of quantum based initialization, selection and IVF crossover with sigmoid mutation

- Managerial insights are drawn depending product quality and disruption on roads

This paper is structured as follows: in Section 1, a brief introduction is given. Section 2 elaborates on TPP model with parameters. In Section 3, we introduce and elaborate presentation of development of quantum-inspired MA (Q_iMA). In Section 4 numerical experiments are performed and results are reported. Finally, we conclude the paper by discussing important research questions addressed, relevance of the insights derived, limitations and future scope of research in Section 5.

1.2. Literature review

The TPP, first introduced by Ramesh [51] in 1981, is a variant of the classical traveling salesman problem (TSP). Early papers on TPP include that of Voß [65], in which a study of a TPP with fixed costs was presented. Two different types of TPP models, biobjective and asymmetric, were developed by Riera-Ledesma and Salazar-González [54, 56]. A budget constraint TPP model was solved by Mansini and Tocchella [41], with capacitated and uncapacitated variations [cf. Mansini and Tocchella [40]]. 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 [13, 14, 15, 16]. Other types of variations of the TPP with multiple stacks and delivery were studied by Batista-Galván et al. [6]. Although a few studies, however, a multiple vehicle TPP was papers implemented; see TPP multiple vehicles Bianchessi et al. [7], Manerba and Mansini [38], and Gendreau et al. [19].

Abdelhalim et al. [1] address a multiple vehicle inventory routing with the fixed time period for perishable products with considering vehicle capacity in transportation. They are optimizing production and transportation cost. A recent study found according to Broekmeulen and van Donselaar [9] by reducing food waste and increasing freshness and sales for perishables products in supermarkets. They consider three products fresh meat, fruits, and vegetables in 27 stores from 3 large retailers in Europe. A centralized decision system for just-in-time shipment policy was developed by Chen [12] for perishable products such as fishes, fruits and vegetables, etc. In most of the studies about perishable products consider three types of deterioration rate. The linear distribution according to Wu et al. [68], Weibull distribution followed by Ali et al. [3], Gong et al. [22], Perry and Stadje [49] and exponential distribution studied by Al Hamadi et al. [2], Sangeetha et al. [58]. Since we fixed some parameters of Weibull distribution in between 0 to 1, and Weibull distribution will degenerate liner as well as exponential distribution also. So in the present study, we consider the deterioration rate followed Weibull distribution with some modifications according to the problem. In transport planning of the purchased product vehicles load, capacity, and initial quality of the product have a major influence in the decay rate of the perishable items which incorporated in the present investigation.

Earlier, Mandal and Maiti [36, 37] formulated a single item inventory model for a breakable unit with stock dependent demand and they assumed that the demand was a linear or non-linear function of current stock level as well as the breakable unit B(q) depended on the current stock level. They did not considered also the multi-items. Later Maiti and Maiti [34, 35] developed some production-inventory/inventory models for breakable items in crisp environment. Though the general form of breakability function was considered. Again Saha et al. [57] consider the rate of breakability per unit time may be a linear or non-linear function of current stock level. Recently, Halder et al. [26] studied breakable items in a transportation problem. In the present study, we formulated the breakability rate with depending on road conditions, load and capacity of the vehicles, distance covered by the vehicles, etc. Since multiple routes with multiple conveyances are available between markets and depots so different road conditions, i.e., disruption due to weather, longitudinal and latitudinal position, etc., are emerges for simplicity we took into account disruption with normal distribution between 0 to 1 as good to bad.

The list of exact optimization approaches for solving a TPP includes the lexicographic search proposed by Ramesh [51], the branch-and-bound method proposed by Singh and van Oudheusden [59], the branch-and-cut approach proposed by Laporte et al. [30], Riera-Ledesma and Salazar-González [56], and Batista-Galván et al. [6], dynamic programming proposed by Gouveia et al. [23] and Kang and Ouyang [29], and constraint programming proposed by Cambazard and Penz [10]. 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 [5]. A survey of this issue was conducted by Manerba et al. [39]. To address the issue of computation time, various metaheuristic and soft computing (proposed by Zadeh [70]) approaches were explored by several researchers. Voß [66] proposed a Tabu search (TS) and simulated annealing (SA) for an uncapicitated TPP generalization with a deterministic purchasing cost. Teeninga and Volgenant [62] considered an improved heuristic for solving a TPP. Riera-Ledesma and Salazar-González [55] proposed a heuristic for the classical TPP. Petersen and Madsen [50] developed a heuristic approach for a multiple-stack TPP. Some other metaheuristic-based implementations include the TS method proposed by El-Dean [17], variable neighborhood search (VNS) proposed by Ochi et al. [46], and the ant colony optimization (ACO) approach proposed by Bontoux and Feillet [8]. Among the metaheuristic approaches for the TPP, we found that GAs are the most widely used soft computing methods. Ochi et al. [47] proposed a parallel GA called GENPAR, based on the island model, for an asymmetric TPP. Goldbarg et al. [21] developed a transgenetic algorithm (TA) for a TPP that depends on horizontal gene transfer and endosymbiosis.

Moscato et al. [44] first time introduced the word Memetic Algorithm (MA) based on the population of cross GA. MAs are represented with different versions like Hybrid Evolutionary Algorithms (Martínez-Estudillo et al. [42], Baldwinian Evolutionary Algorithms Baldwin [4], Lamarckian Evolutionary Algorithms Skinner [60]). When we merge the rules of memetics and computational model in a frame is called Memetic Computing (MC) introduced by Ong et al. [48]. The nature of MC indicates the nature of the generality of Darwinism. Wang et al. [67] proposed an effective MA to solve TSP based on two improved Inver-over operators, which used different operators in different stages, and improve the convergence speed. Merz and Freisleben [43] focus on his paper, the fitness landscapes of several instances of the TSP are investigated using new generic recombination-based MAs can exploit the correlation structure for finding near-optimum tours for the TSP. Ghoseiri and Sarhadi [20] introduced a special designed MA to solve the well-known Symmetric TSP by using a local search combined with a specially designed genetic algorithm to focus on the population of local optima and good convergence behavior and solutions. Zou et al. [72] presented a novel MA, in which a new local search scheme is introduced called Multi-Local Search each of which executes with a predefined probability to increase the diversity of the population to solve TSP. Gutin and Karapetyan [25] introduced MA with a powerful local search procedure approach to solving generalized TSP which is an extension of the well-known TSP. In 2013, Castro et al. [11] introduced an MA for the TSP with hotel selection (TSPHS). Very recently, Lu et al. [33] studied an MA for the Orienteering Problem with Mandatory Visits and Exclusionary Constraints. Very few kinds of literature are found about quantum inspired MA for solving to TSP or such $NP-hard$ problems. A comprehensive survey about the quantum-inspired evolutionary algorithm was done by Zhang [71]. According to Ganjefar and Tofighi [18] developed a quantum-inspired neural network extended over a hybrid GA which is the combination of the gradient descent method for solving the optimization problem. But they did not investigate any quantum experiment on GA. In the present study, we extended the GA operators such as selection, and crossover depends on quantum behavior. An MA with real observation based quantum-inspired evolutionary algorithm (QIEA) proposed by Liu et al. [32] to solve reactive power optimization in power systems. Yuanyuan and Xiyu [69] proposed a QIEA for automatically determine the cluster and optimizing the solutions. Best of our knowledge, we do not found any quantum-inspired MA to solve such TSP or TPP.

2. Proposed Multi-depot 4D Traveling Purchaser Problem (multi-depot 4DTPP)

We create a table of important parameters with their descriptions that we use frequently in subsequent sections.

Abbreviation and description of parameters and decision variables

Notation	Description
K	Product Set
M	Market Set
C(i,j)	Traveling cost from ith market to jth market
a_{mk}, c_{mk}	Unit cost of loss at m^{th} depot for perishable and breakable product k
C_{io}^{ft}	Unit transporting cost from ith market to depot using vehicle type f
e_{io}^{f}	Emission rate of vehicle per unit length
q_{ik}	Availability of kth product at ith market
p_{ik}	Purchase cost of kth product at ith market
p_c	Possibility of crossover
p_m	Possibility of mutation
d_{ik}	Demand of k^{th} item at i^{th} market
w_i	Per unit Weights of product i
x_{el}	Decision variable for traveling l^{th} type of vehicles corresponding edge e
x_{erl}	Decision variable for traveling r^{th} route using l^{th} type of vehicles corresponding edge e
y_i	Decision variables of the selecting the corresponding market i
$\acute{x}_{ef}$	Decision variable for transporting f^{th} type of vehicles corresponding edge e
$\grave{x}_{esf}$	Decision variable for transporting by s^{th} route using f^{th} type of vehicles through edge e

2.1. 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 mathematical formulation is

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

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

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

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

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

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

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

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

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

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.

2.2. Modified Three Dimensional Travelling Purchaser Problem (Solid/3D TPP)

Previously defined symbols in TPP formulation will be continued while describing formulation of our chosen problem context. In our solid TPP, different vehicle types are available to travel to different markets as well as to transport the purchased products from every market to depot. Here, c_{el} defines traveling cost from i^{th} market to j^{th} market with $\{e = (i,j)\}$ using l^{th} type of conveyance, $l \in \{l : 1, 2, \cdots, L\}$. Similarly c_{i0}^{ft} recognizes the unit transportation cost from i^{th}

market to depot 0 using vehicle type $f = \{f : 1, 2, \cdots, F\}$. Mathematical formulation of solid TPP is as follows:

2.2.1. Scenario-I: Goods are transported directly to depot just after purchase

$$
\begin{gathered}
Z_1 = \sum_{e \in E} (c_{el}) x_{el} + \sum_{k \in K} \sum_{i \in M_k} p_{ik} z_{ik} \\
Z_2 = \sum_{e \in E} \sum_{i \in M_k} c_{i0}^{ft} \acute{x}_{ef} \\
\text{Minimize } Z = Z_1 + Z_2 \\
Where \quad l \in \{1, 2, \cdots, L\}, f \in \{1, 2, \cdots, F\}.
\end{gathered}
\tag{10}
$$

with Equs. 3-9.

2.2.2. Scenario-II: Goods are transported with purchaser by a separate vehicle

$$
\begin{gathered}
\text{Minimize } Z_1 = \sum_{e \in E} (c_{el}) x_{el} + \sum_{k \in K} \sum_{i \in M_k} p_{ik} z_{ik} \\
Z_2 = \sum_{e \in E} \sum_{i \in M_k} c_{e}^{ft} x_{ef} \\
\text{Minimize } Z = Z_1 + Z_2 \\
Where \quad l \in \{1, 2, \cdots, L\}, f \in \{1, 2, \cdots, F\}.
\end{gathered}
\tag{11}
$$

with Equs. 3-9.

2.3. Multi-depot Four Dimensional Travelling Purchaser Problem (multi-depot 4DTPP)

Instead of single depot considering multiple depots set $m = \{0, 1, 2, \cdots, P-1\}$ for simplicity here staring depot is always 0. In our Four Dimensional TPP, different routes are available to travel to different markets as well as to transport the purchased products from every market to depot. Here, c_{erl} defines traveling cost from i^{th} market to j^{th} market with $\{e = (i, j)\}$ through r^{th} route using l^{th} type of conveyance, $r \in \{1, 2, \cdots, R\}$ and $l \in \{1, 2, \cdots, L\}$. Similarly c_{ism}^{ft} recognizes the unit transportation cost from i^{th} market to depot m through s^{th} route, $s \in \{l : 1, 2, \cdots, S_1\}$ using vehicle type $f = \{f : 1, 2, \cdots, H\}$. Mathematical formulation of m-depot 4DTPP for $Scenario-I$ is as follows:

$$
\begin{gathered}
\text{Minimize Z} = \sum_{e \in E} (c_{erl}) x_{erl} + \sum_{k \in K} \sum_{i \in M_k} p_{ik} z_{ik} + \sum_{e \in E,} \sum_{i \in M_k} c_{ism}^{ft} \grave{x}_{esf} \\
Where \quad l \in \{1, 2, \cdots, L\}, f \in \{1, 2, \cdots, F\}, r \in \{1, 2, \cdots, R\}, \\
s \in \{1, 2, \cdots, S_1\}, m = \{0, 1, 2, \cdots, P-1\}.
\end{gathered}
\tag{12}
$$

$$
\grave{x}_{esf} \in \{0, 1\}, \;\; e \in E, \;\; s \in \{1, 2, \cdots, S_1\}, f \in \{1, 2, \cdots, H\}. \tag{13}
$$

with Equs. 2-9.

2.4. Multi-depot 4DTPP with Perishable and Breakable items

It is observed that, some products are perishable such as vegetables, fruits, fish, etc. some are breakable such as dry fruit- cashew, biscuits, etc. and rest of the both perishable come breakable like as egg, sweets, etc. Even some of the products are incompatible also. Here consider

$K = \acute{K} \cup \acute{\acute{K}}$, $\acute{K} = \{\text{Perishable Products}\}$, $\acute{\acute{K}} = \{\text{Breakable Products}\}$, and $\acute{K} \cap \acute{\acute{K}}$= Both perishable and breakable products. So all of these taking into account the mathematical model formulated as given below:

$$
\begin{aligned}
&\text{Minimize Z}= \sum_{e\in E} (c_{erl})x_{erl} + \sum_{k\in K}\sum_{i\in M_k} p_{ik}z_{ik} + \sum_{k\in \acute{K}}\sum_{i\in M_k} (a_{mk} * \theta_{ik})z_{ik} \\
&\quad + \sum_{k\in \acute{\acute{K}}}\sum_{i\in M_k} (c_{mk} * \Omega_{ik})z_{ik} + \sum_{e\in E,}\sum_{i\in M_k} c^{ft}_{ism}\grave{x}_{esf} \\
&Where \quad l \in \{1, 2, \cdots, L\}, f \in \{1, 2, \cdots, H\}, r \in \{1, 2, \cdots, R\}, \\
&\quad s \in \{1, 2, \cdots, S_1\}, m = \{0, 1, 2, \cdots, P-1\}.
\end{aligned}
\tag{14}
$$

θ_{ik} is the perishable rate at i^{th} market for k^{th} perishable product given below:

$$
\begin{gathered}
\theta_{ik} = \begin{cases} \xi_{k_0}, & Q_{ik} = 1 \\ \xi_{k_0} * (1 - Q_{ik})^{-n^f * t * \xi_k}, & 0 < Q_{ik} < 1 \end{cases} \\
\xi_k = \frac{1}{T_k}, \\
T_k = Shelf\ life\ of\ the\ k^{th}\ product \\
n^f = \frac{w^f}{W^f}, w^f = Present\ load\ of f^{th}\ Vehicle, \\
W^f = Maximum\ load\ capacity\ f^{th}\ type\ of\ vehicle, \\
Q_{ik_0} = Initial\ quality\ of\ the\ k^{th}\ product\ at\ i^{th}\ market, \\
t = Required\ transporting\ time.
\end{gathered}
\tag{15}
$$

Ω_{ik} is the breakability rate at i^{th} market for k^{th} breakable product given below:

$$
\begin{gathered}
\Omega_{ik} = n^f * (R_c + v_c) * \log(1 + \tfrac{1}{d})^d \\
n^f = \frac{w^f}{W^f}, w^f = Present\ load\ of f^{th}\ Vehicle, \\
W^f = Maximum\ load\ capacity\ f^{th}\ type\ of\ vehicle, \\
R_c = Road\ condition\ (disruption), 0 < R_c < 1 \\
v_c = vehicle\ condition, 0 < v_c < 1 \\
d\ is\ the\ distance\ will\ be\ carried.
\end{gathered}
\tag{16}
$$

Here we taken as Q_{ik} is the quality of the products and 1 stands for highest (good) and 0 for worst quality (i.e, completely perishable) of the product. Similarly, R_c and v_c which are taken as 0 for road and vehicle condition is good and 1 indicated route is mostly disrupted and vehicles is bad. For simplicity, R_c and v_c are randomly generated following normal distribution in between 0 and 1.

3. Proposed Quantum-inspired Memetic Algorithm (Q_iMA)

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_iMA, 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 [27]). 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. [61]):

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{17}$$

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

$$||\alpha||^2 + ||\beta||^2 = 1 \tag{18}$$

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 memetic algorithm (Q_iMA)

Here, we propose a quantum-inspired GA (Q_iMA) that uses the quantum initialization and selection, an IVF crossover, and generation-dependent sigmoid mutation. The proposed Q_iMA 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

$$\alpha_{ij} = \mu * \frac{C_{ij}}{S_i} - \nu * \frac{A_j}{SA_i}, i, j = 1, 2, \cdots, n. \tag{19}$$

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. 19, 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. 18. 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. 18 and 19.

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.

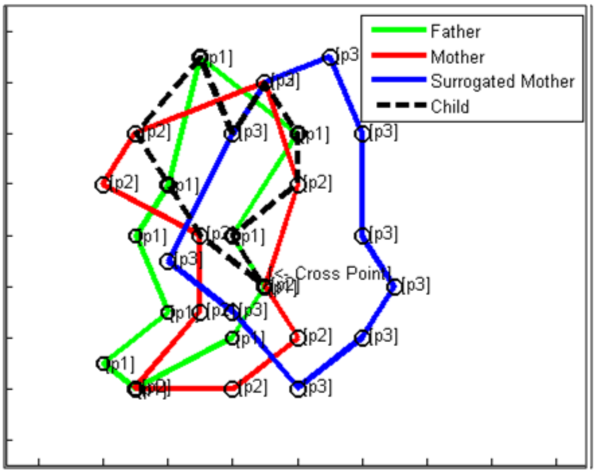


Figure 1: In vitro fertilization crossover.

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_iMA

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

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

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_iMA

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 TSPLIB

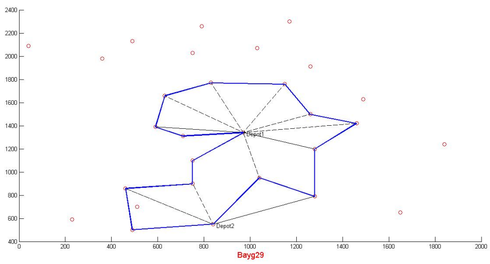
This section establishes the effectiveness of proposed metaheuristic by comparing the results with traditional GA on benchmark instances. We have taken standard benchmark problems from Reinelt [52] repository. We introduce capacity (or availability) of each market by generating a random number in a range ensuring that total depot demand cannot be met by one market. Table 1 illustrates results in terms of solution quality and computational time. The percentage values represent the improvement of Q_iMA over traditional one using the formula $\frac{Cost_{GA-Trad}-Cost_{Q_iMA}}{Cost_{GA-Trad}} * 100$ %, where $Cost_{Q_iMA}$ and $Cost_{GA-Trad}$ denote the costs obtained by running Q_iMA and traditional GA respectively. For effective comparison, we have selected benchmark problem instances between 100 to 202 cities with market capacity values 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. Difference in CPU times column reports the time difference between traditional GA and Q_iMA to obtain the best solution. Considering numbers of depots 1, 5, 10 and 20 respectively. From the results, it is evident that Q_iMA performs better than traditional GA in terms of solution quality with significant reduction in computational time.

How the multi-depots are significantly distributed and shared the markets that are found in the present figures. In the Figure 2 shows that the market planning for the different problem for

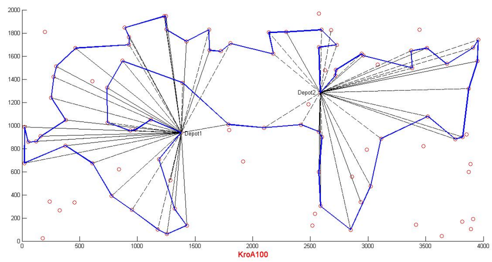
List of parameters with values chosen for numerical experiment

Parameters	Domain Value/Range	Parameters	Domain Value/Range
Number of Chromosome	50-150	T_k	85 hr/unit
Max_Initialization	100-500	θ_{ik_0}	-
Max_Generation	300-1000	p_{ik}	-
p_c	0.20-0.75	a_{mk}	-
p_m	0.01-0.20	ξ_k	-
Qubit Initialization Limit	0.51-0.75	ξ_{k_0}	-
Qubit Selection Limit	0.61-0.75	d	-
Number of Chromosome	50-150	t	-
Max_Initialization	100-500	Ω_{ik}	0-1
Max_Generation	300-1000	R_c	0-1
p_c	0.20-0.75	V_c	0-1
p_m	0.01-0.20	d	
θ_{ik}	0-1	η_{ik}	0-1
ξ_k	–	ψ	-
Q_{ik}	0-1		
n^f	0-1	d_k	10%-90%
w^f	–	q_0	0-1
W^f	–		-

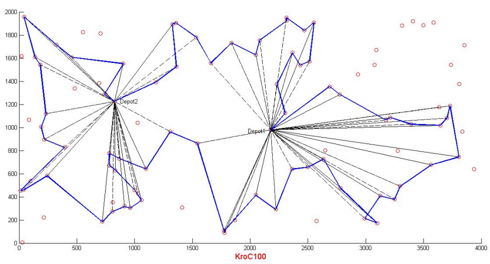
29 nodes in Figure 2(a) and 100 nodes problem in Figure 2(b), Figure 2(c) and 200 nodes problem in Figure 2(d) with two depot under availability 70-100 units of each products.



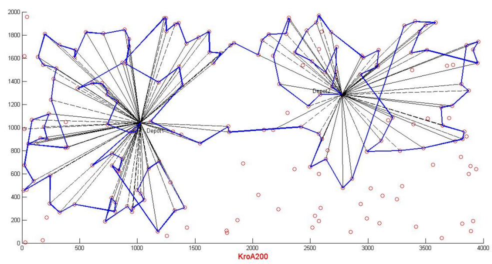
(a) Market planning for Bayg29



(b) Market planning for kroA100



(c) Market planning for kroC100



(d) Market planning for kroA200

Figure 2: Market planning for benchmark problems

Table 1: Comparison of Q_iMA and traditional GA on benchmark instances

Algorithm	Instance	Depot	Worst (%)	Avg (%)	Best (%)	Difference in Cpu time (seconds)
Q_iMA & GA	KorA100	1	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	3187
Q_iMA & GA	KorA100	5	1.05	1.78	0.13	1256
	kroB100		3.41	0.31	0.45	1865
	kroC100		0.35	0.06	0.32	1534
	kroD100		1.87	0.85	1.13	1783
	kroE100		0.75	1.102	0.49	1534
	eil101		0.055	0.47	0.054	1479
	lin105		0.42	0.14	0.021	2018
	gr120		0.18	0.87	0.54	1691
	kroA150		0.014	0.08	0.72	1359
	kroB150		0.19	0.76	0.002	2971
	ch150		0.17	0.97	1.21	3215
	gr202		0.054	0.74	0.015	3152
Q_iMA & GA	KorA100	10	0.32	0.71	0.01	1146
	kroB100		1.01	0.017	0.01	1574
	kroC100		0.24	0.56	0.015	1892
	kroD100		1.46	0.97	1.08	1564
	kroE100		0.082	0.95	0.028	1279
	eil101		0.01	01.78	0.43	1658
	lin105		0.018	0.003	0.84	2058
	gr120		0.178	0.298	0.671	2175
	kroA150		0.087	0.91	0.009	1296
	kroB150		0.75	0.19	0.87	2584
	ch150		1.54	0.95	0.018	2053
	gr202		0.98	0.51	0.07	3286
Q_iMA & GA	KorA100	15	1.57	1.84	0.92	1687
	kroB100		1.78	1.06	0.91	2357
	kroC100		1.01	0.97	2.54	3208
	kroD100		2.58	1.87	1.35	2017
	kroE100		1.04	1.51	0.74	1657
	eil101		0.57	0.92	0.88	1895
	lin105		0.97	1.09	0.58	2875
	gr120		0.098	0.07	0.75	3021
	kroA150		0.025	0.81	0.079	2015
	kroB150		0.21	0.67	0.87	3457
	ch150		0.15	0.28	0.14	3124
	gr202		1.31	1.02	1.32	5188
Q_iMA & GA	KorA100	20	2.12	1.52	1.15	2241
	kroB100		2.13	1.97	0.87	2973
	kroC100		0.56	0.21	0.91	2812
	kroD100		1.98	2.51	2.73	2654
	kroE100		1.21	1.85	0.65	2138
	eil101		0.015	01.25	0.001	1779
	lin105		1.05	1.21	0.64	4577
	gr120		1.02	1.51	1.034	3751
	kroA150		0.57	1.84	0.41	2452
	kroB150		0.32	0.87	0.25	4521
	ch150		0.72	0.51	0.12	3862
	gr202		1.71	0.28	1.81	5582

4.2. m-depot 4DTPP

4.2.1. Availability in multi-depot 4DTPP

In the present section, we study the different parameters with their importance relevant to the model. The importance of the availability of the products with chosen of numbers of markets are found in Figure 3(a) again the pricing strategy with uniform and different number market visits sharply visible in Figure 3(b). Now the availability increases and corresponding transportation cost decreases which found in Figure 3(c). In Figure 3(d) shows that higher capacity vehicles are chosen as availability increases. The product quality is an important factor of this investigation since low-quality product in very short time goes to perishable, so the markets are chosen in that area where quality is goods as well as availability also high which got in the Figure 3(f).

4.2.2. Perishability in multi-depot 4DTPP

Here the relevance of the perishability is established with the Figure 4. In Figure 4(a), shows that the perishability cost effect the selection of transportation vehicles. Again the total cost of perishability is decreased when product quality increases which founds in figure 4(b). Again the road disruption is measure role in perishability that given in Figure 4(c).

4.3. Disruption in multi-depot 4DTPP

In this section, we study the disruption in vehicles and roads. Since between two markets multiple paths are available with different road condition so disruption creates the different procurement policies. In Figure 5(a), numbers of chosen markets are initially increase but not steady when disruption increases. Similar style founds in Figure 5(b) where changes of path and disruption presented. Again low disruption rate influence the procurement manager to choose the markets near about the depot. Most of the markets centered to the depot given in Figure 5(c). Road conditions also motivated the appropriate vehicles selection because in high disrupted zone low capacity vehicles produces more breakable products which founds in the Figure 5(d). Lastly in Figure 5(e), average product quality increases as disruption increases sharply.

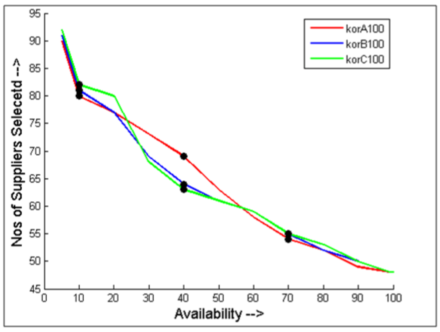
4.4. Breakability in multi-depot 4DTPP

Here we investigate the breakability condition depends on road, vehicles and distance from the depot. In Figure 6(a) found the types vehicles scenario changed. Again road condition influences the breakablity of the product firmly shows in Figure 6(b) and Figure 6(c) identify that when average distance from depot to the market increases corresponding brekability of the product increases.

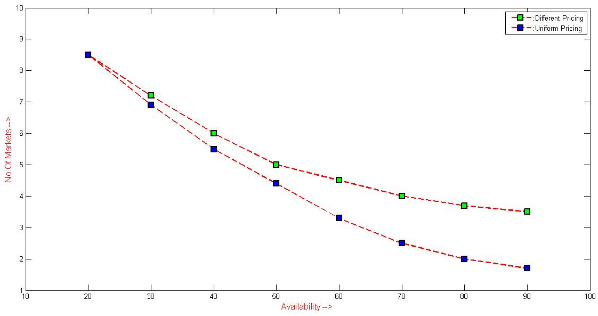
5. Conclusion

In this paper, we develop a quantum initialization and selection with an IVF crossover memetic algorithm with generation dependent sigmoid mutation to solve a multi-depot multi path traveling purchaser problem with perishable and breakable items under disruptions.

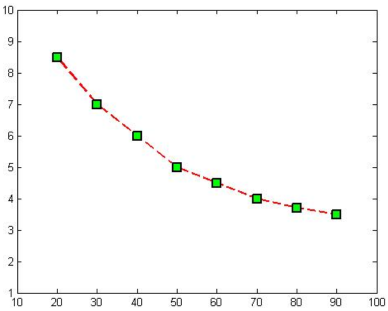
Our problem directly relates to any typical purchasing and distribution problem valid for sourcing organizations. It can also be used in other optimization applications like network optimization, graph theory, solid transportation problems, production planning, vehicle routing. While the standard model description involves multiple markets with varying purchase prices and distance matrix to understand the traveling cost, our problem improves on it in many ways. Firstly we introduce multiple central warehouses (called multi-depots) to which the purchased



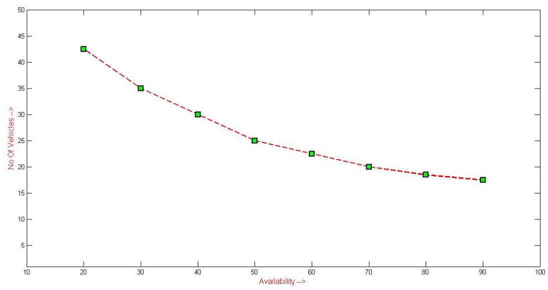
(a) Availability Vs Market Visit



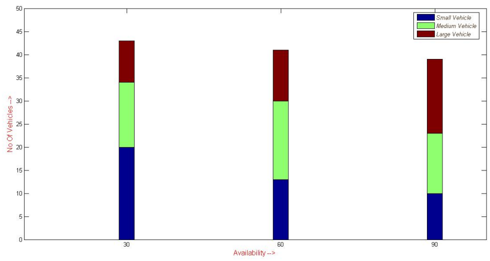
(b) Availability Vs Pricing Strategy



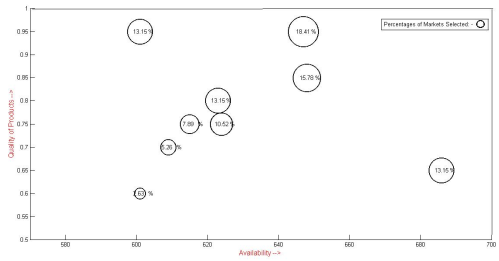
(c) Availability Vs Transportation Cost



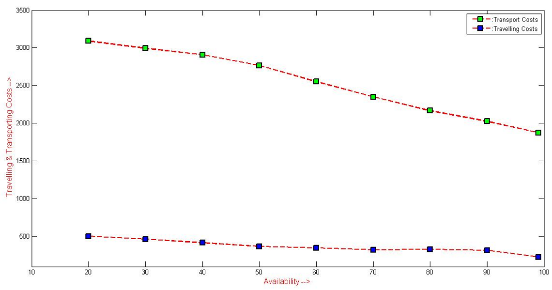
(d) Availability Vs Vehicles Choose



(e) Availability vs No of Vehicles

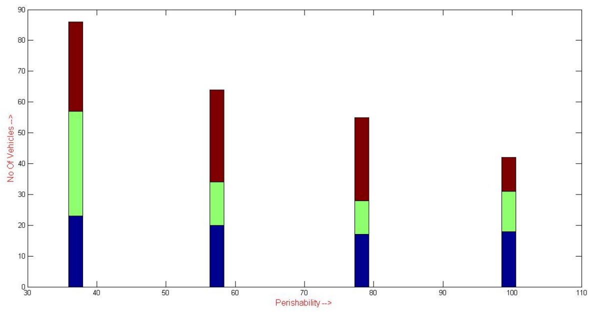


(f) Availability Vs Product Quality

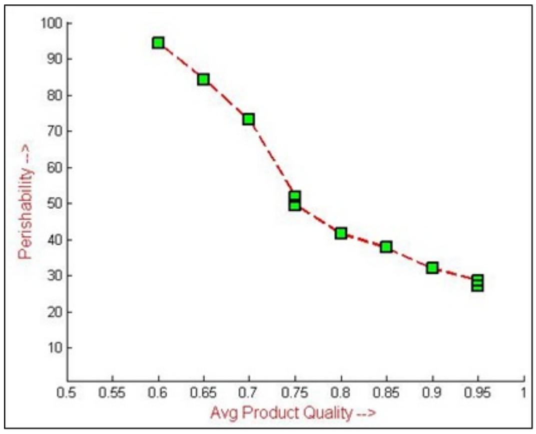


(g) Availability vs Traveling and Transporting Cost

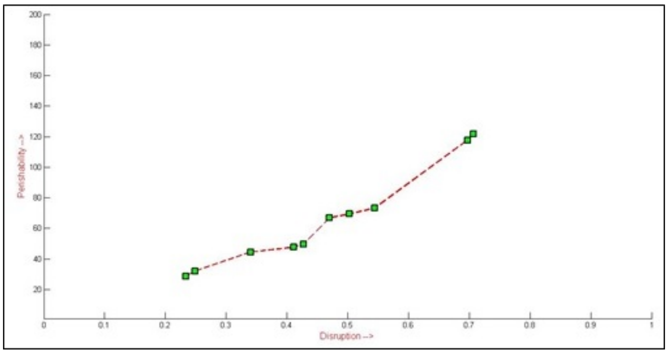
Figure 3: Availability Vs Different Parameters



(a) Perishability Vs Number of Vehicles

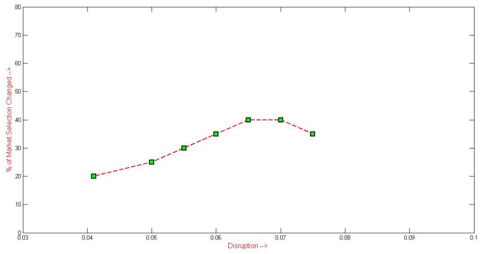


(b) Perishability Vs Product Quality

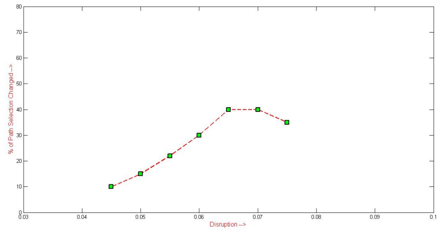


(c) Perishability Vs Disruption

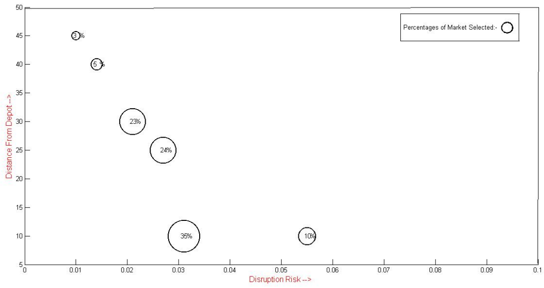
Figure 4: Perishability Vs Vehicles, Product Quality,and Risk Factors



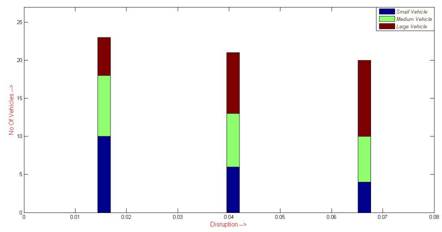
(a) Disruption vs Market Selection



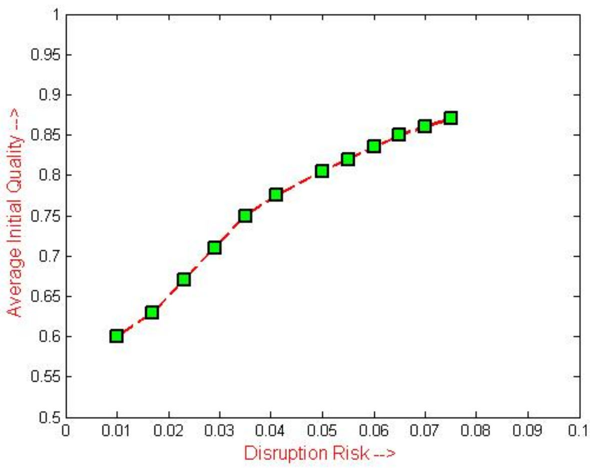
(b) Disruption vs Path Selection



(c) Disruption vs Distance from Depot

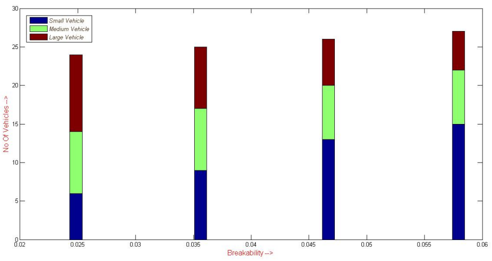


(d) Disruption vs Vehicles Selection

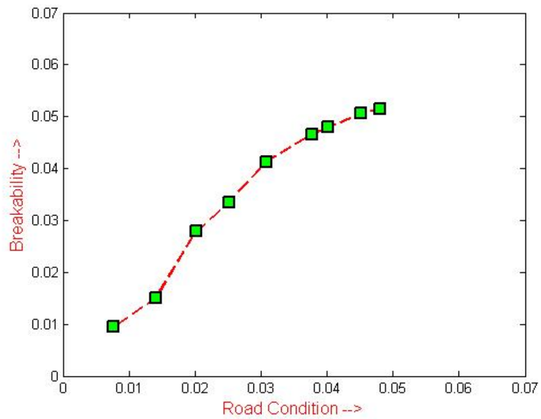


(e) Disruption vs Product Quality

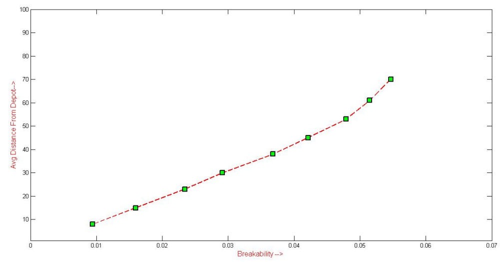
Figure 5: Disruption vs Market, Path, Distance from Depot, Vehicle selection and quality of product



(a) Breakability Vs No Of Vehicles



(b) Breakability Vs Road Condition



(c) Breakability Vs Average Distance from depot

Figure 6: Breakability

products will be despatched. This adds one more cost component, i.e., transportation cost, to minimize. Between markets and depots, multiple routes and vehicles are included in the present investigation which makes a more realistic one. We have considered a capacitated version of the problem by restricting the market availability randomly decided within a range. In the product types considering perishable and breakable items which depend on a different vehicle, road, initial quality, etc., specific parameters. Our first contribution is in making a methodological improvement by developing quantum inspired GA (Q_iMA) with IVF crossover technique and sigmoid mutation. With minor customization, we believe that Q_iMA will emulate similar success in other combinatorial optimization problems. We have clearly established its dominance over traditional GA in terms of solution quality and computational time.

Practically purchase managers try to exploit the arbitrage opportunity from differential purchase prices across markets. For this kind of complex problems, GA should be followed by a post-optimization procedure that we did not incorporate. For example, while doing a crossover, we identify a market position and swap the set of markets from this position onward. While this is fine for route optimization considering traveling cost, a post-optimization process is necessary to understand whether the same set of transporting vehicles will be valid for the revised solution or not.

References

[1] Abdelhalim, A., Eltawil, A., and Fors, M. N. (2015). The multiple vehicle inventory routing problem for perishable products. In *Industrial Engineering and Engineering Management (IEEM), 2015 IEEE International Conference on*, pages 1169–1173. IEEE.

[2] Al Hamadi, H. M., Sangeetha, N., and Sivakumar, B. (2015). Optimal control of service parameter for a perishable inventory system maintained at service facility with impatient customers. *Annals of Operations Research*, 233(1):3–23.

[3] Ali, S. S., Madaan, J., Chan, F. T., and Kannan, S. (2013). Inventory management of perishable products: a time decay linked logistic approach. *International Journal of Production Research*, 51(13):3864–3879.

[4] Baldwin, J. M. (1896). A new factor in evolution (continued). *The American Naturalist*, 30(355):536–553.

[5] Barketau, M. and Pesch, E. (2016). An approximation algorithm for a special case of the asymmetric travelling salesman problem. *International Journal of Production Research*, 54(14):4205–4212.

[6] Batista-Galván, M., Riera-Ledesma, J., and Salazar-González, J. J. (2013). The traveling purchaser problem, with multiple stacks and deliveries: A branch-and-cut approach. *Computers & Operations Research*, 40(8):2103–2115.

[7] Bianchessi, N., Mansini, R., and Speranza, M. G. (2014). The distance constrained multiple vehicle traveling purchaser problem. *European Journal of Operational Research*, 235(1):73–87.

[8] Bontoux, B. and Feillet, D. (2008). Ant colony optimization for the traveling purchaser problem. *Computers & Operations Research*, 35(2):628–637.

[9] Broekmeulen, R. A. and van Donselaar, K. H. (2017). Quantifying the potential to improve on food waste, freshness and sales for perishables in supermarkets. *International Journal of Production Economics*.

[10] Cambazard, H. and Penz, B. (2012). A constraint programming approach for the traveling purchaser problem. In *Principles and practice of constraint programming*, pages 735–749. Springer.

[11] Castro, M., Sörensen, K., Vansteenwegen, P., and Goos, P. (2013). A memetic algorithm for the travelling salesperson problem with hotel selection. *Computers & Operations Research*, 40(7):1716–1728.

[12] Chen, Z. (2018). Optimization of production inventory with pricing and promotion effort for a single-vendor multi-buyer system of perishable products. *International Journal of Production Economics*, 203:333–349.

[13] Choi, M. and Lee, S. (2009). Periodic heterogeneous multiple traveling purchaser problem for refuse logistics optimization. *Journal of the Korean Society of Supply Chain Management*, 9(2):147–154.

[14] Choi, M.-J. and Lee, S.-H. (2010a). Heterogeneous multiple traveling purchaser problem with budget constraint. *Journal of the Korean Operations Research and Management Science Society*, 35(1):111–124.

[15] Choi, M.-J. and Lee, S.-H. (2010b). Uncapacitated multiple traveling purchaser problem. *Journal of Korean Institute of Industrial Engineers*, 36(2):78–86.

[16] Choi, M. J. and Lee, S. H. (2011). The multiple traveling purchaser problem for maximizing systems reliability with budget constraints. *Expert Systems with Applications*, 38(8):9848–9853.

[17] El-Dean, R. A.-H. Z. (2008). A tabu search approach for solving the travelling purchase problem. In *Proceedings of the international conference on informatics and system, INFOS2008*, pages 24–30. Citeseer.

[18] Ganjefar, S. and Tofighi, M. (2018). Optimization of quantum-inspired neural network using memetic algorithm for function approximation and chaotic time series prediction. *Neurocomputing*, 291:175–186.

[19] Gendreau, M., Manerba, D., and Mansini, R. (2016). The multi-vehicle traveling purchaser problem with pairwise incompatibility constraints and unitary demands: A branch-and-price approach. *European Journal of Operational Research*, 248(1):59–71.

[20] Ghoseiri, K. and Sarhadi, H. (2008). A memetic algorithm for symmetric traveling salesman problem. *International Journal of Management Science and Engineering Management*, 3(4):275–283.

[21] Goldbarg, M. C., Bagi, L. B., and Goldbarg, E. F. G. (2009). Transgenetic algorithm for the traveling purchaser problem. *European Journal of Operational Research*, 199(1):36–45.

[22] Gong, W., Li, D., Liu, X., Yue, J., and Fu, Z. (2007). Improved two-grade delayed particle swarm optimisation (tgdpso) for inventory facility location for perishable food distribution centres in beijing. *New Zealand Journal of Agricultural Research*, 50(5):771–779.

[23] Gouveia, L., Paias, A., and Voß, S. (2011). Models for a traveling purchaser problem with additional side-constraints. *Computers & Operations Research*, 38(2):550–558.

[24] Gutierrez, M. M., Meleddu, M., and Piga, A. (2017). Food losses, shelf life extension and environmental impact of a packaged cheesecake: A life cycle assessment. *Food Research International*, 91:124–132.

[25] Gutin, G. and Karapetyan, D. (2010). A memetic algorithm for the generalized traveling salesman problem. *Natural Computing*, 9(1):47–60.

[26] Halder, S., Das, B., Panigrahi, G., and Maiti, M. (2017). Some special fixed charge solid transportation problems of substitute and breakable items in crisp and fuzzy environments. *Computers & Industrial Engineering*, 111:272–281.

[27] Han, K.-H. and Kim, J.-H. (2002). Quantum-inspired evolutionary algorithm for a class of combinatorial optimization. *IEEE transactions on evolutionary computation*, 6(6):580–593.

[28] Hindustantimes (2018). Fdi rules in food retail.

[29] Kang, S. and Ouyang, Y. (2011). The traveling purchaser problem with stochastic prices: Exact and approximate algorithms. *European Journal of Operational Research*, 209(3):265–272.

[30] Laporte, G., Riera-Ledesma, J., and Salazar-González, J.-J. (2003). A branch-and-cut algorithm for the undirected traveling purchaser problem. *Operations Research*, 51(6):940–951.

[31] Lawler, E., Lenstra, J., Rinnooy Kan, A., and Shmoys, D. (1985). The traveling salesman problem: Ge re guided tour of combinatorial optimization,(1985).

[32] Liu, H., Zhang, G., Liu, C., and Fang, C. (2008). A novel memetic algorithm based on real-observation quantum-inspired evolutionary algorithms. In *Intelligent System and Knowledge Engineering, 2008. ISKE 2008. 3rd International Conference on*, volume 1, pages 486–490. IEEE.

[33] Lu, Y., Benlic, U., and Wu, Q. (2018). A memetic algorithm for the orienteering problem with mandatory visits and exclusionary constraints. *European Journal of Operational Research*, 268(1):54–69.

[34] Maiti, M. K. and Maiti, M. (2005). Inventory of damageable items with variable replenishment and unit production cost via simulated annealing method. *Computers & Industrial Engineering*, 49(3):432–448.

[35] Maiti, M. K. and Maiti, M. (2006). Multi-item shelf-space allocation of breakable items via genetic algorithm. *Journal of Applied Mathematics and Computing*, 20(1-2):327–343.

[36] Mandal, M. and Maiti, M. (1997). Inventory model for damagable items with stock-dependent demand and shortages. *Opsearch*, 34(3):155–166.

[37] Mandal, M. and Maiti, M. (1999). Inventory of damagable items with variable replenishment rate, stock-dependent demand and some units in hand. *Applied Mathematical Modelling*, 23(10):799–807.

[38] Manerba, D. and Mansini, R. (2015). A branch-and-cut algorithm for the multi-vehicle traveling purchaser problem with pairwise incompatibility constraints. *Networks*, 65(2):139–154.

[39] Manerba, D., Mansini, R., and Riera-Ledesma, J. (2017). The traveling purchaser problem and its variants. *European Journal of Operational Research*, 259(1):1–18.

[40] Mansini, R. and Tocchella, B. (2009a). Effective algorithms for a bounded version of the uncapacitated tpp. In *Innovations in Distribution Logistics*, pages 267–281. Springer.

[41] Mansini, R. and Tocchella, B. (2009b). The traveling purchaser problem with budget constraint. *Computers & Operations Research*, 36(7):2263–2274.

[42] Martínez-Estudillo, A. C., Hervás-Martínez, C., Martínez-Estudillo, F. J., and García-Pedrajas, N. (2005). Hybridization of evolutionary algorithms and local search by means of a clustering method. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 36(3):534–545.

[43] Merz, P. and Freisleben, B. (2001). Memetic algorithms for the traveling salesman problem. *Complex Systems*, 13(4):297–346.

[44] Moscato, P. et al. (1989). On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms. *Caltech concurrent computation program, C3P Report*, 826:1989.

[45] Narayanan, A. and Moore, M. (1996). Quantum-inspired genetic algorithms. In *Evolutionary Computation, 1996., Proceedings of IEEE International Conference on*, pages 61–66. IEEE.

[46] Ochi, L. S., Drummond, L., and Figueiredo, R. (1997). Design and implementation of a parallel genetic algorithm for the travelling purchaser problem. In *Proceedings of the 1997 ACM symposium on Applied computing*, pages 257–262. ACM.

[47] Ochi, L. S., Vianna, D. S., Drummond, L. M., and Victor, A. O. (1998). A parallel evolutionary algorithm for the vehicle routing problem with heterogeneous fleet. In *International Parallel Processing Symposium*, pages 216–224. Springer.

[48] Ong, Y.-S., Lim, M. H., and Chen, X. (2010). Memetic computationast, present & future [research frontier]. *IEEE Computational Intelligence Magazine*, 5(2):24–31.

[49] Perry, D. and Stadje, W. (2000). Inventory systems for goods with censored random lifetimes. *Operations Research Letters*, 27(1):21–27.

[50] Petersen, H. L. and Madsen, O. B. (2009). The double travelling salesman problem with multiple stacks–formulation and heuristic solution approaches. *European Journal of Operational Research*, 198(1):139–147.

[51] Ramesh, T. (1981). Traveling purchaser problem. *Opsearch*, 18(1-3):78–91.

[52] Reinelt, G. (1995). Tsplib http://www. iwr. uni-heidelberg. de/groups/comopt/software. *TSPLIB95*.

[53] Report, C. R. P. (2018). Corporate responsibility progress report 2016/17.

[54] Riera-Ledesma, J. and Salazar-González, J. J. (2005a). The biobjective travelling purchaser problem. *European Journal of Operational Research*, 160(3):599–613.

[55] Riera-Ledesma, J. and Salazar-González, J. J. (2005b). A heuristic approach for the travelling purchaser problem. *European Journal of Operational Research*, 162(1):142–152.

[56] Riera-Ledesma, J. and Salazar-González, J.-J. (2006). Solving the asymmetric traveling purchaser problem. *Annals of Operations Research*, 144(1):83–97.

[57] Saha, A., Roy, A., Kar, S., and Maiti, M. (2010). Inventory models for breakable items with stock dependent demand and imprecise constraints. *Mathematical and Computer Modelling*, 52(9-10):1771–1782.

[58] Sangeetha, N., Sivakumar, B., and Arivarignan, G. (2015). Optimal control of production time of perishable inventory system with finite source of customers. *Opsearch*, 52(3):412–430.

[59] Singh, K. N. and van Oudheusden, D. L. (1997). A branch and bound algorithm for the traveling purchaser problem. *European Journal of operational research*, 97(3):571–579.

[60] Skinner, M. K. (2015). Environmental epigenetics and a unified theory of the molecular aspects of evolution: a neo-lamarckian concept that facilitates neo-darwinian evolution. *Genome biology and evolution*, 7(5):1296–1302.

[61] Talbi, H., Draa, A., and Batouche, M. (2004). A new quantum-inspired genetic algorithm for solving the travelling salesman problem. In *Industrial Technology, 2004. IEEE ICIT'04. 2004 IEEE International Conference on*, volume 3, pages 1192–1197. IEEE.

[62] Teeninga, A. and Volgenant, A. (2004). Improved heuristics for the traveling purchaser problem. *Computers & Operations Research*, 31(1):139–150.

[63] Thomson, G. B. (2017). Food date labels and hunger in america. *Concordia L. Rev.*, 2:143.

[64] Times, E. (2018). Amazon goes shopping for future retail.

[65] Voß, S. (1989). The traveling purchaser problem with fixed costs. *Arbeitspapier, TH Darmstadt, Fachgebiet Operations Research*.

[66] Voß, S. (1996). Dynamic tabu search strategies for the traveling purchaser problem. *Annals of Operations Research*, 63(2):253–275.

[67] Wang, Y.-t., Li, J.-q., Pan, Q.-k., Sun, J., and Ren, L.-q. (2010). Memetic algorithm based on improved inver-over operator for tsp. In *Natural Computation (ICNC), 2010 Sixth International Conference on*, volume 5, pages 2386–2389. IEEE.

[68] Wu, J., Skouri, K., Teng, J.-T., and Hu, Y. (2016). Two inventory systems with trapezoidal-type demand rate and time-dependent deterioration and backlogging. *Expert Systems with Applications*, 46:367–379.

[69] Yuanyuan, M. and Xiyu, L. (2018). Quantum inspired evolutionary algorithm for community detection in complex networks. *Physics Letters A*.

[70] Zadeh, L. (1994). Fuzzy logic and soft computing: Issues, contentions and perspectives. In *Proc. IIZUKA*, volume 94, pages 1–2.

[71] Zhang, G. (2011). Quantum-inspired evolutionary algorithms: a survey and empirical study. *Journal of Heuristics*, 17(3):303–351.

[72] Zou, P., Zhou, Z., Chen, G., and Yao, X. (2004). A novel memetic algorithm with random multi-local-search: A case study of tsp. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 2335–2340. IEEE.