Bulk wheat transportation and storage problem of Public Distribution System

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Abstract:

This research investigates the multi-period multi-modal bulk wheat transportation and storage problem in a two-stage supply chain network of Public Distribution System (PDS). The bulk transportation and storage can significantly curtail the transit and storage losses of food grains, which leads to substantial cost savings. A mixed integer non-linear programming model (MINLP) is developed after studying the Indian wheat supply chain scenario, where the objective is to minimize the transportation, storage and operational cost of the food grain incurred for efficient transfer of wheat from producing states to consuming states. The cost minimization of Indian food grain supply chain is a very complex and challenging problem because of the involvement of the many entities and their constraints such as seasonal procurement, limited scientific storages, varying demand, mode of transportation and vehicle capacity constraints. To address this complex and challenging problem of food grain supply chain, we have proposed the novel variant of Chemical Reaction Optimization (CRO) algorithm which combines the features of CRO and Tabu search (TS) and named it as a hybrid CROTS algorithm (Chemical reaction optimization combined with Tabu Search). The numerous problems with different sizes are solved using the proposed algorithm and obtained results have been compared with CRO. The comparative study reveals that the proposed CROTS algorithm offers a better solution in less computational time than CRO algorithm and the dominance of CROTS algorithm over the CRO algorithm is demonstrated through statistical analysis.

Keywords: Transportation-storage problem; Food grain supply chain; Public Distribution System; Mixed integer non-linear programming; Chemical reaction optimization.

1. Introduction

The population of India is continuously increasing because of that demand of wheat is also growing. Therefore, for fulfilling the ever-growing demand of wheat there is a necessity of more production, more procurement and proper storage and transportation methods. The wheat production in India has steadily increased due to the use of advanced agricultural production technologies. Food grain is distributed to weaker and vulnerable sections of society at reasonable prices through PDS which is the national food security system of India. Transportation and storage system of food grain become very complex because of the 4, 89,000

Fair Price shops (FPS) located at different parts of the country. Furthermore, it is the largest retail system of its type in the world. The higher losses of wheat occurred during transit and storage because of improper storage and conventional method of transportation through gunny bags.

The various operations of Food Corporation of India (FCI) comprises of procurement, storage, transportation and distribution of food grains on behalf of the Government of India (GOI). FCI is a central nodal agency responsible for the execution of all these activities. The Fig. 1 shows the detail operations of FCI from procurement at minimum support price (MSP) from farmers to the sale of food grains to consumers at a central issue price (CIP). The procurement is carried out in two stages i.e. centralized and decentralized procurement. In the centralized procurement, FCI along with state government agencies (SGAs) procures the wheat for the central pool from the farmers in the procurement centers at MSP. Procured wheat is stored in the FCIs warehouses, including State Warehousing Corporation (SWC) and the Central Warehousing Corporation (CWC) warehouses of producing states. In decentralized procurement (DCP), SGAs procures food grains but they directly store into their warehouses and distribute under PDS based on the allocation of GOI. In a centralized system after procurement, the goal is to transfer the wheat to deficit states warehouses from producing state warehouses. The GOI makes the allocation to the respective states based on the demand of that states and offtakes in the previous period. Distribution of food grains to consumers is totally handled by respective consuming states. The transportation of food grains in intrastate is mostly carried out by road and interstate movement through rail in conventional gunny bags. Furthermore, primarily the wheat supply chain involved the transportation, handling and storage cost and to reduce these costs, it needs the efficient movement of food grains from producing to consuming states.

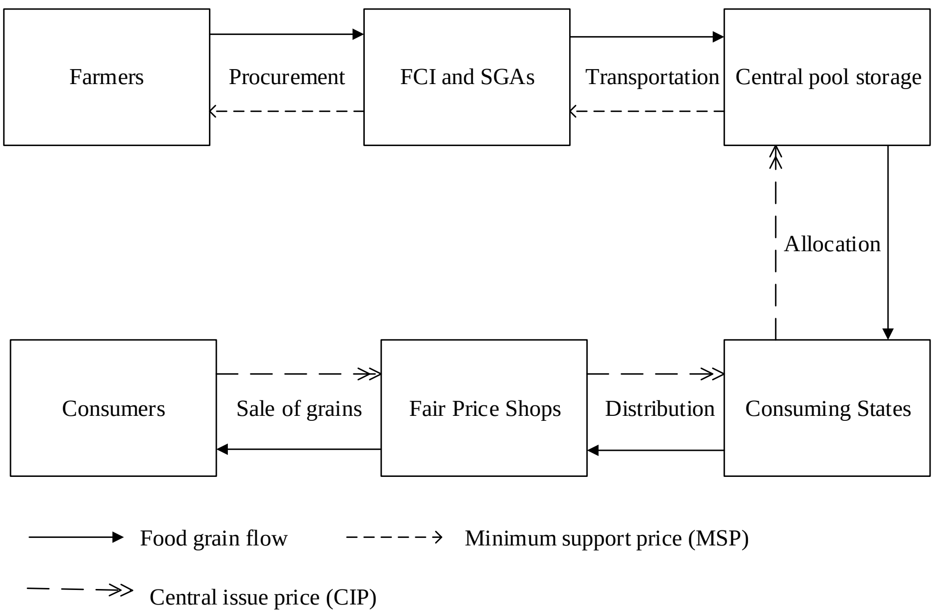

Fig. 1. FCI Operations

At present, FCI is facing several major issues and challenges with food grain storage, transportation and distribution. FCI daily transports an average 2 million bags (50 kg per bag) of food grains through rail, road and waterways from producing to consuming states covering an average 1500 km distance. The annual transportation cost incurred for this movement was 47.2737 billion INR mentioned in Comptroller and Auditor General of India (CAG, 2013) report. According to the report of the Institution of Mechanical Engineers (2013), India every year losses wheat near about 21 million tons, which is equivalent to the total wheat production of a country like Australia. As per CAG 2013 report, overall 45% food grains are getting wasted from the post-harvest to distribution stage due to lack of proper handling, transportation and infrastructure. The monetary value of these losses amounts to more than Rs 50,000 crores per year (Singh 2010). There is a significant discrepancy in the procured quantity and storage capacity available with FCI. As mentioned in the CAG 2013 report, the food grains stock in the central pool as on 1st June 2012 was 667.89 Lakh Metric Tonne (LMT) barring the DCP against the aggregate FCI capacity of 491.86 LMT including SWC and CWC capacities. This wide gap of 176.03 LMT stockpiling limit shows the requirement of more storage capacity to cope with growing procurement. Generally, procurement of wheat is carried out during Rabi marketing season (April-June) by SGAs, therefore, more storage capacity requires during this peak period. FCI needs to assume control over the stock from SGAs toward the end of June, but unfortunately, because of the absence of available storage capacity, FCI can't lift the stock from SGAs and for keeping this stock beyond the time limit FCI gives the carry over charges to SGAs. FCI has given the Rs 175 crore in 2006-07 and Rs 1635 crore for the period of 2011-12 as a carry over charges to various SGAs across the country. The above-discussed issues can be addressed through bulk storage and transportation of food grain instead of conventional gunny bags. However, in the present situation FCI and all other agencies have less number of scientific storages in each state. Therefore, proper planning and management of bulk wheat transportation and storage reduces the food grain supply chain cost.

In this paper, we consider the real problem of bulk wheat transportation and storage in India. Generally, wheat transportation has been carried out from producing states to consuming states. The main focus of this paper is on the development of a mathematical model for cost minimization considering bulk wheat transportation and storage with deterministic demand and procurement. The transportation of food grain from producing state to consuming state become the challenging task because of the limited number of steel silos. Apart from this issue, other constraints which makes the problem very complex such as the availability of various capacitated vehicles, fixed cost associated with each vehicle, operational cost, and optimal inventory level, etc. Indian food grain supply chain is categorized into four stages. The primary stage includes transportation of food grains from procurement centers to silos in producing states and shipment from these silos to consuming states silos is the second stage. The subsequent stages include grain shipment up to block level and from block level to fair price shops. There are some major important issues which affects the transportation and distribution cost of wheat such as "how much quantity, from which origin node, when and where to transport". Besides, inventory and operational cost of wheat inside the silos play the vital role in the food grain supply chain cost. Generally, interstate food grain transportation is carried out by rail mode, but in some cases, it transports through road mode also if economical. Hence, selection of the mode of transportation is also a crucial aspect of the food grain supply chain.

The remainder of the paper is structured as follows. Section 2 provides the details of existing available literature of transportation problem, food supply chain, and Evolutionary Algorithms (EAs). Section 3 gives the description of the considered problem. Section 4 shows the mathematical model formulation of the problem. Section 5 describes the solution methodology used in the paper. Results and analysis of the paper are presented in section 6. Section 7 concludes the paper and gives the future direction of the research.

2. Literature Review

The inventory transportation problem of supply chain network is an interesting topic and a plethora of literature available on the same. The literature review has been divided into two sections. The initial section covers the literature related to transportation and storage problem and subsequent section focuses mainly on the various solution approaches used in literature for solving these problems.

2.1 Transportation and storage models

Asgari et al. (2013) solved the real world optimization problem of wheat storage and transportation in Iran, where they have developed a linear integer programming (LIP) model. The objective of this model was to minimize the storage and transportation cost of wheat. Furthermore, they used the warehouse preference constraints for filling wheat like high-quality warehouse should be filled first and then medium, low quality. However, they have not considered the rail road flexibility, vehicle capacity, and availability constraint. They have suggested the memetic and TS algorithm for future work to solve this type of problems. Etemadnia et al. (2015) investigated a wholesale facility (hub) locations model in U.S. fruit and vegetables supply chain systems on a national scale for efficient transfer of food where they have examined the bimodal (land and air) food transportation system. In the perspective of steel silos, Tefera et al. (2011) critically reviewed strengths and possible effects of metal silo technology for reducing the post-harvest losses and also the involvement of various international organizations on implementation of this technology in the developing countries. These international organizations have successfully implemented metal silo technology in Kenya and Malawi for maize and bean storage purpose. Furthermore, Maiyar et al. (2015) addressed the food grain shipment problem of Indian PDS considering the railroad flexibility in their mathematical model. However, they have not taken into account the inventory cost of food grains and vehicle capacity constraint. Ma et al. (2011) studied the problem of shipment consolidation and transportation through cross docking distribution network by taking care of vehicles set up cost, time window constraint and trade-offs between transportation costs, inventory and time scheduling requirements. Kopanos et al. (2012) addressed the multiproduct, multi-site production and distribution planning problem simultaneously in the semicontinuous food industries. They optimally solved the two industrial case studies of emerging Greek dairy industry.

Musa, Arnaout, and Jung (2010) addressed the transportation problem of cross docking network and solved the integer programming model using novel Ant Colony Optimization

(ACO) algorithm. But, in their model, they have not assessed the scenario of multi-period optimization, and availability of different capacitated vehicles. Berman and Wang (2006) analyzed the distribution strategy selection problem for distribution of a family of products from suppliers to plants, where the objective was to minimize the transportation, pipeline inventory and plant inventory cost. The milk run strategy, different types of trucks and less than full truck load strategy have not been taken into consideration. Ahumada and Villalobos (2009) comprehensively reviewed the state of literature, primarily on production and distribution planning models which were successfully implemented for agri-foods based on agricultural crops. The different models were categorised on the basis of optimization approaches used, types of crops and scope of plans. Jawahar and Balaji (2009) investigated the fixed charge two-stage distribution problem, in which Genetic Algorithm (GA) results compared with approximate and lower bound solutions. The spanning tree based genetic algorithm (st-GA) was introduced by Jo et al. (2007) to tackle the non-linear fixed charge transportation problem (NFCTP), where they have represented the transportation problem as network problem because of its feasible nature of spanning tree. In the spanning tree based research, Hajiaghaei-Keshteli et al. (2010) presented the pioneer method for designing the chromosomes, which are feasible for getting the best solutions of NFCTP. They have also carried out the robust calibration of the parameters using Taguchi method and compared the performance of presented algorithm with the LINGO performance. However, they have not considered the dynamic environment and trucks availability constraint of the problem. Kutanoglu and Lohiya (2008) developed the integrated inventory/ transportation optimization model which was tactical in nature and based on base stock inventory model. Moreover, they considered single echelon and multi-facility service parts logistics system through time-based service level constraints. Jawahar and Balaji (2012) extended fixed charge transportation problem (FCTP) to multi-period context, where they have taken into account the backorders and inventories. They have formulated the pure integer nonlinear programming and 0-1 mixed integer linear programming (MILP) mathematical models and solutions of the GA based heuristic compared with LINGO solver, lower bounds and approximate solutions. The priority based genetic algorithm (pb-GA) with a novel crossover and mutation operators was suggested by Lotfi and Tavakkoli-Moghaddam (2013) for the linear and NFCTP. They have compared the result of pb-GA with the st-GA and shown that pb-GA was more suitable for solving NFCTP.

Mousavi et al. (2014) examined the integrated location and seasonal inventory problem of two-stage supply chain network through a modified particle swarm optimization (PSO) algorithm and results were validated using GA. Çetinkaya et al. (2009) presented the integrated cost minimization outbound logistics model of Frito lay's in the form of large scale, multi-product inventory lot-sizing and vehicle routing MILP model. Furthermore, the coordinated inventory transportation planning problem of a single supplier and multiple retailers was addressed by Kang and Kim (2010), where the mixed integer model with minimization of objective function has been solved using the two-phase heuristic algorithm. In the perspective of vehicle capacity and availability related constraint, they have assumed all homogenous vehicles and unlimited availability of vehicles. Lamsal, Jones, and Thomas (2016) developed the mathematical model for the movement of the crop from farm to processing plants by considering the multiple independent farmers and no storage exists at the farm. This study mainly focused on sugar cane, sugar beets, and vegetable crops. The problem has been solved using a two-phase solution approach with decomposition. Ge, Gray, and Nolan (2015) identified the various quality testing strategies of wheat in a Canadian complex operational and regulatory environment with the help of analytic and agent-based simulation models. Moreover, the minimization of handling cost of the wheat supply chain using these strategies was the main goal of these models.

2.2 Solution approaches

Nowadays, the application of EAs to tackle several transportation-related problems is continuously growing because mostly these types of problems belongs to Non-deterministic Polynomial-time (NP) hard category. In order to get the exact solutions of this NP-hard and big size problems is very difficult, so EAs at least gives the near optimal solutions. Masson et al. (2016) developed a two-stage method established on an adaptive large neighbourhood search (ALNS) for designing the optimal route for collection of milk from farm to processing plants of dairy transportation problem in Canada. They have solved the transportation and plant assignment problem in first and second phase, respectively. Xie and Jia (2012) proposed the efficient hybrid genetic algorithm (HGA) called non-linear fixed charge transportation problem-hybrid genetic algorithm (NFCTP-HGA) to solve the NFCTP and they evaluated the performance of the proposed algorithm on two large size problems by comparing with LINGO results. Adlakha and Kowalski (2003) presented a simple heuristic for small scale fixed charge transportation problem, which finds the best initial solution in the first part and improvement in solution along with verification of optimality in the second part. Panicker et al. (2013) developed the ACO based heuristic for solving the fixed charge two stage distribution-allocation problem considering a single product, single period and infinite capacity of the distributors. The heuristic has been tested on benchmark problems from the literature and obtained solutions verified with GA based heuristic. Also, they statistically confirmed the superiority of ACO based heuristic over the GA based heuristic using the paired comparison t-test. In the same domain, Antony Arokia Durai Raj and Rajendran (2012) proposed GA as a solution approach for the two stage FCTP by considering the variable and fixed cost of transportation along with unlimited distributor capacity in first scenario and the opening cost of Distribution Center (DC), variable cost from plant to DC and DC to customers are focused in the second scenario.

Most of the EAs are nature inspired, but Lam and Li (2010) developed the metaheuristic called Chemical Reaction Optimization (CRO) which inspired from the chemical reactions of molecules. They have employed CRO for solving well-known NP-hard problems, including Quadratic Assignment Problem (QAP), Resource-Constrained Project Scheduling Problem (RCPSP) and Channel Assignment Problem (CAP). Furthermore, they have shown the effectiveness of CRO among the few other metaheuristics by solving different optimization problems. In recent times, Choudhary et al. (2015) developed the non-linear programming model with the objective of maximization of quadratic profit function which handles the trade-off between twin challenges i.e., pressure of regulatory penalties and reduced demand, of monopolist firm serving to the environmental sensitive market and solved by the CRO. The multi-objective flexible job-shop scheduling problem was evaluated by Li and Pan (2012), where the objective function includes the minimization of maximal completion time, total workload, and maximal workload with preventive and non-preventive maintenance constraints. They solved the multi-objective problem using the proposed discrete chemical reaction optimization (DCRO) algorithm. Furthermore, Li and Pan (2013) solved the same problem with fuzzy processing time and flexible maintenance activities using the hybrid chemical reaction optimization (HCRO). They have incorporated the TS based local search operator in the proposed algorithm for improving the convergence ability. Initially, Xu et al. (2013) developed a Double Molecular Structure-based chemical reaction optimization (DMSCRO) technique for solving the Directed Acyclic Graph (DAG) scheduling problem in heterogeneous computing systems. Furthermore, in 2015 they have developed an HCRO algorithm for minimizing the time overhead of same DAG scheduling problem (Xu et al. 2015). They have employed the CRO for the DAG task scheduling and heuristics algorithms are applied for mapping the tasks to processors. The artificial chemical reaction optimization (ACROA) algorithm comprises of new repair operator with greedy strategy and random selection has been proposed for solving the 0-1 knapsack problem (Truong et al. 2015). Therein, the superior performance of the proposed algorithm has been demonstrated by comparing the results with GA and quantum-inspired evolutionary algorithm.

Although, there is a very vast literature available on TS algorithm, we have focused mainly on the articles which are relevant to this paper. Recently, an efficient TS with new tabu rules for decreasing the computational time was proposed by the Abyazi-Sani and Ghanbari (2016) for solving the uncapacitated single allocation hub location problem and tested the algorithm on standard Operations Research Library **(**ORLIB) instances. Furthermore, the large-scale multi-echelon supply chain network redesign problem was studied by Melo et al. (2012) and solved the MILP model of facility relocation multi-period optimization problem through TS heuristic. To improve the performance of CRO, a hybrid algorithm called CROTS was proposed by Yan et al. (2015) for solving the well-known NP-complete 0-1 knapsack problem. The effectiveness of CROTS over the GA and CRO has been demonstrated through the experimental results. The single objective optimization problems were efficiently solved using the hybrid particle swarm-chemical reaction optimization (HP-CRO) by combining two local search operators e.g. PSOupdate operator and local search operator (Nguyen et al. 2014). A tactical integrated production-distribution problem with multiple products over finite planning horizon has been addressed by Armentano, Shiguemoto, and Løkketangen (2011). They have determined the production quantity of each product and quantity of each product to be delivered to the customer along with routes of the vehicles. Their objective was to minimize the production and holding cost at the plant, holding cost at the customer and distribution costs. Furthermore, they have proposed the two variants of TS with short term and long term memory for solving the problem.

In the domain of food supply chain, very few studies have been carried out for transportation and storage related problems and limited to the problem of the production inventory transportation system of manufacturing industries. The food grains transportation and storage problem has given very less attention in the previous literature. These studies are mostly limited to transportation and inventory cost only, but we have focused on 1. Operational cost of wheat inside the silos 2. Capacitated warehouses and vehicles and 3. Multi-period and multi-modal environment. Operational cost is mainly the movement cost of wheat from starting point to end point of modern steel silos. The capacitated warehouses and vehicles, as well as multi-period environment aspects of the transportation problem, have not been very effectively addressed in the literature. Therefore, in this paper, to capture the reality various capacitated and limited number of each type of vehicles are considered for bulk wheat transportation.

3. Problem Background

In this paper, we have captured the real time scenario of bulk wheat storage and transportation of Indian PDS in a finite time period. As explained initially, the wheat is procured from farmers at MSP during Rabi marketing season at several procurement centers located at a various part of the district. In order to fully utilize the large capacitated vehicles and minimize the transportation cost, foremost important is the clustering of procurement centers and in this problem each origin node is represented as a cluster of procurement centers. Two stage food grain supply chain network of bulk wheat storage and transportation problem has been shown in the Fig. 2, where the transportation of wheat from an origin node to silos is carried out using trucks. The next stage is the transportation of wheat from silos to destination nodes of consuming states using rail or road mode. We also assumed that silos should maintain a certain level of inventory during each time period. Selection of the number of vehicles for food grain transportation depends on the fixed cost associated with each of the vehicle.

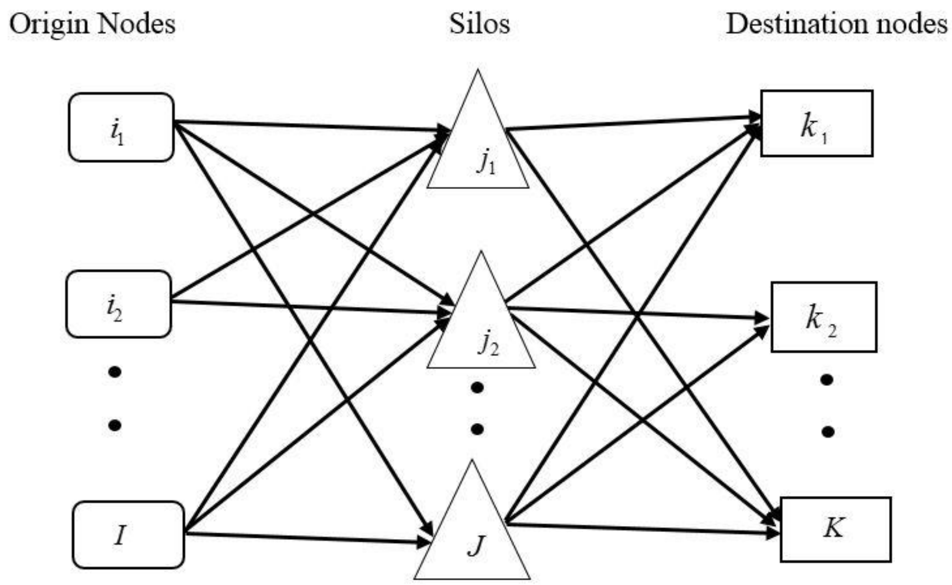

Fig. 2. Two stage bulk wheat supply chain network

Furthermore, in this problem we are focusing on the scenario where wheat is transported from major producing states like Punjab, Haryana, Madhya Pradesh, Uttar Pradesh, and Rajasthan to the major wheat consuming states such as Maharashtra, Tamilnadu, Karnataka, and West Bengal in India. The overall objective of this problem is to make the time-dependent storage and movement plan to minimize the transportation, inventory and operational cost at origin nodes, silos and destination nodes, respectively. The detail formulation of this problem is illustrated in the next section.

4. Problem Formulation

The detail description of assumptions considered in model, sets, indices, parameters and decision variables are given at the beginning of model. The objective function followed by the several constraints of the problem is explained at a later stage of the formulation.

Assumptions:

- Each origin node i is a cluster of procurement centers.
- Demand of destination nodes is deterministic in nature and well known with little variation.
- Number of each truck types, rake types and their availability are finite.
- The shipment costs are considered with the travelled distances only not with traveling time among locations.
- The procured quantity of wheat is sufficient to satisfy the demand of each destination nodes.
- The demand of each given destination node k is to be satisfied during that period using either rail or road transportation.

Notations:

Sets:

T	Set of Time periods
I	Set of origin nodes i. e. cluster of procurement centers
J	Set of Silos
K	Set of destination nodes
X	Set of inbound trucks between origin nodes and silos
Y	Set of rakes between silos and destination nodes
Z	Set of outbound trucks between silos and destination nodes

Indices:

t	Time periods
i	Origin node
j	Silo
k	Destination node
x	Inbound trucks

y Rakes

z Outbound trucks

α Road

β Rail

Parameters:

v_i^{xt} Number of x types of inbound trucks available at i^{th} origin node during time period t $\left(i \in I, x \in X, t \in T\right)$

l_j^{yt} Number of y types of rakes available at j^{th} silo during time period t $\left(j \in J, y \in Y, t \in T\right)$

h_j^{zt} Number of z types of outbound trucks available at j^{th} silo during time period t $\left(j \in J, z \in Z, t \in T\right)$

u_x Capacity of inbound trucks of type x $\left(x \in X\right)$

e_y Capacity of rakes of type y $\left(y \in Y\right)$

g_z Capacity of outbound trucks of type z $\left(z \in Z\right)$

s_x Fixed cost for inbound trucks of type x on arc $\left(i, j\right)$ $\left(x \in X\right)$

q_y Fixed cost for rakes of type y on arc $\left(j, k\right)$ $\left(y \in Y\right)$

f_z Fixed cost for outbound trucks of type z on arc $\left(j, k\right)$ $\left(z \in Z\right)$

w_j Inventory holding cost per Metric Tonne (MT) quantity of wheat per unit time in j^{th} silo $\left(j \in J\right)$

c_{ij}^{α} Shipment cost per MT wheat quantity per km transported by road from i^{th} origin node to j^{th} silo $\left(i \in I, j \in J\right)$

c_{jk}^{β} Shipment cost per MT wheat quantity per km transported by rail from j^{th} silo to k^{th} destination node $\left(j \in J, k \in K\right)$

c_{jk}^{α} Shipment cost per MT wheat quantity per km transported by road from j^{th} silo to k^{th} destination node $\left(j \in J, k \in K\right)$

V_j Operational cost per MT wheat quantity at j^{th} silo $\left(j \in J\right)$

D_k^t Demand of k^{th} destination node in period t $\left(k \in K, t \in T\right)$

d_{ij}^{α} Distance from i^{th} origin node to j^{th} silo by road. $\left(i \in I, j \in J\right)$

d_{jk}^{β} Distance from j^{th} silo to k^{th} destination node by rail. $\left(j \in J, k \in K\right)$

d_{jk}^{α} Distance from j^{th} silo to k^{th} destination node by road. $\left(j \in J, k \in K\right)$

Q_i^t Wheat quantity available at i^{th} cluster during period t $\left(i \in I, t \in T\right)$

R_j Capacity of j^{th} silo $\left(j \in J\right)$

Decision variables:

Binary Variables

$$G_{ij}^t \quad \begin{cases} 1 & \text{if } i^{th} \text{ origin node is assigned to } j^{th} \text{ silo during period } t; \\ 0 & \text{otherwise.} \end{cases}$$

$$E_{jk}^t \quad \begin{cases} 1 & \text{if } j^{th} \text{ silo is assigned to } k^{th} \text{ destination node during period } t; \\ 0 & \text{otherwise.} \end{cases}$$

$$\sigma_{jk}^{\beta t} \quad \begin{cases} 1 & \text{if rail is used to transport wheat to assigned } k^{th} \text{ destination node} \\ & \quad \text{from } j^{th} \text{ silo in time } t; \\ 0 & \text{otherwise.} \end{cases}$$

$$\delta_{jk}^{\alpha t} \quad \begin{cases} 1 & \text{if road is used to transport wheat to assigned } k^{th} \text{ destination node} \\ & \quad \text{from } j^{th} \text{ silo in time } t; \\ 0 & \text{otherwise.} \end{cases}$$

Wheat quantity transported and stored:

$a_{ij}^{\alpha t}$ Wheat quantity transported from i^{th} origin node to j^{th} silo by road during time period t $\left(i \in I, j \in J, t \in T\right)$

$m_{jk}^{\beta t}$ Wheat quantity transported from j^{th} silo to k^{th} destination node by rail during time period t $\left(j \in J, k \in K, t \in T \right)$

$b_{jk}^{\alpha t}$ Wheat quantity transported from j^{th} silo to k^{th} destination node by road during time period t $\left(j \in J, k \in K, t \in T \right)$

B_j^t Quantity of wheat in j^{th} silo at time t $\left(j \in J, t \in T \right)$

Number of trucks and rakes used:

r_{ij}^{xt} number of x types of trucks used from i^{th} origin node to j^{th} silo during time period t $\left(i \in I, j \in J, x \in X, t \in T \right)$

n_{jk}^{yt} number of y types of rakes used from j^{th} silo to k^{th} destination node during time period t $\left(j \in J, k \in K, y \in Y, t \in T \right)$

p_{jk}^{zt} number of z types of trucks used from j^{th} silo to k^{th} destination node during time period t $\left(j \in J, k \in K, z \in Z, t \in T \right)$

Objective function:

Min Total cost =

$$\sum_{i \in I} \sum_{j \in J} \sum_{x \in X} \sum_{t \in T} \left[\left(s_x r_{ij}^{xt} \right) + \left(d_{ij}^{\alpha} c_{ij}^{\alpha} a_{ij}^{\alpha t} \right) \right] G_{ij}^t + \sum_{j \in J} \sum_{k \in K} \sum_{y \in Y} \sum_{t \in T} \left[\left(q_y n_{jk}^{yt} \right) + \left(d_{jk}^{\beta} c_{jk}^{\beta} m_{jk}^{\beta t} \right) \right] E_{jk}^t \sigma_{jk}^{\beta t} +$$
$$\sum_{j \in J} \sum_{k \in K} \sum_{z \in Z} \sum_{t \in T} \left[\left(f_z p_{jk}^{zt} \right) + \left(d_{jk}^{\alpha} c_{jk}^{\alpha} b_{jk}^{\alpha t} \right) \right] E_{jk}^t \delta_{jk}^{\alpha t} + \sum_{t \in T} \left[\sum_{i \in I} \sum_{j \in J} a_{ij}^{\alpha t} + \sum_{j \in J} \sum_{k \in K} \left(m_{jk}^{\beta t} + b_{jk}^{\alpha t} \right) \right] V_j + \sum_{j \in J} \sum_{t \in T} w_j B_j^t \quad (1)$$

Subject to

$$\sum_{j \in J} a_{ij}^{\alpha t} G_{ij}^t \leq Q_i^t , \qquad \forall i, \forall t \qquad (2)$$

$$\sum_{k \in K} \left(m_{jk}^{\beta t} E_{jk}^t + b_{jk}^{\alpha t} E_{jk}^t \right) \leq B_j^t \qquad \forall j, \forall t \qquad (3)$$

$$\sum_{j\in J}\left(m_{jk}^{\beta t}E_{jk}^{t}+b_{jk}^{\alpha t}E_{jk}^{t}\right)=D_{k}^{t} \qquad \forall k,\forall t \tag{4}$$

$$B_{j}^{t-1}+\sum_{i\in I}a_{ij}^{\alpha t}G_{ij}^{t}\le R_{j} \qquad \forall j,\forall t \tag{5}$$

$$B_{j}^{t-1}+\sum_{i\in I}a_{ij}^{\alpha t}G_{ij}^{t}-\sum_{k\in K}\left(m_{jk}^{\beta t}E_{jk}^{t}+b_{jk}^{\alpha t}E_{jk}^{t}\right)=B_{j}^{t} \qquad \forall j,\forall t \tag{6}$$

$$B_{j}^{t=1}=0 \qquad \forall j,\forall t \tag{7}$$

$$E_{jk}^{t}=\ \sigma_{jk}^{\beta t}\ +\ \delta_{jk}^{\alpha t} \qquad \forall j,\ \forall k,\ \forall t \tag{8}$$

$$\sum_{j\in J}a_{ij}^{\alpha t}G_{ij}^{t}\le\sum_{j\in J}\sum_{x\in X}r_{ij}^{xt}u_{x} \qquad \forall i,\forall t \tag{9}$$

$$\sum_{k\in K}\left(m_{jk}^{\beta t}E_{jk}^{t}+b_{jk}^{\alpha t}E_{jk}^{t}\right)\le\sum_{k\in K}\sum_{y\in Y}\sum_{z\in Z}\left(n_{jk}^{yt}e_{y}+p_{jk}^{zt}g_{z}\right) \qquad \forall j,\forall t \tag{10}$$

$$G_{ij}^{t},E_{jk}^{t},\sigma_{jk}^{\beta t},\delta_{jk}^{\alpha t}=\{0,1\} \qquad \forall i,\forall j,\forall k,\forall t \tag{11}$$

$$a_{ij}^{\alpha t},m_{jk}^{\beta t},b_{jk}^{\alpha t},B_{j}^{t}\ge 0 \qquad \forall i,\forall j,\forall k,\forall t \tag{12}$$

$$\begin{array}{l} r_{ij}^{xt},n_{jk}^{yt},p_{jk}^{zt}\in N_{0} \\ \text{where } N_{0}=\{0,1,2,3....\}\end{array} \qquad \forall i,\forall j,\forall k,\forall x,\forall y,\forall z,\forall t \tag{13}$$

The objective function (1) minimizes the total cost which involves five terms. The first term represents the fixed and variable cost of transportation from origin nodes to silos. The second and third term describes the fixed and variable cost incurred for bulk wheat transportation from silos to assigned destination nodes through rail or road, respectively. The next term corresponds to the movement cost of wheat inside the silos. The last term denotes the inventory holding cost in silos.

Constraint (2) make sure that amount of wheat transported from each origin node is less than or equal to the wheat quantity available during that period. Constraint (3) ensures that the total wheat quantity shipped from each silo through either rail or road is less than or equal to the available quantity at the silo in each time period. Demand satisfaction of the destination node is represented by the constraint (4). Furthermore, the constraint (5) defines the silo storage capacity for each time period. Constraint (6) depicts the inventory flow balance equation. Constraint (7) represents the initial inventory in each silo at the starting time period is zero. Constraint (8) guarantees that wheat must be shipped only on assigned nodes using either rail or road transportation. It means that if assignment variable E_{jk}^{t} become one (assignment is there) then either rail or road transportation should be selected. In other case, if assignment variable becomes zero then no mode will be selected. Constraints (9) describe the truck capacity constraint for the wheat shipment between origin nodes to silos. Similarly, constraint (10) shows the rake or truck capacity constraint for wheat transportation between silos and destination nodes. The binary, continuous and non-negative integer variables are represented by constraints (11), (12) and (13) respectively.

The FCTP is much more difficult to solve due to the presence of fixed cost which cause discontinuities (nonlinear) in the objective function and is known to be NP-hard (Antony Arokia Durai Raj and Rajendran 2012; Balaji and Jawahar, 2010; Gen, Altiparmak and Lin, 2006; Jawahar and Balaji, 2009; Jawahar and Balaji, 2012; Klose, 2008; Panicker et al. 2013; Xie and Jia 2012). This problem is also belong to the category of FCTP. Moreover, the difficulty has been increased due to the inclusion of multi-modal and time-dependent inventories in the problem. Normally, the exact solution algorithm such as branch and bound solves the small size problems and it takes excessive computational time, hence to solve the large size problems with reasonable computational time several heuristics are developed and reported by many authors in the literature. In order to solve the non-linear programming problems, generally several random search optimization techniques such as GA, simulated annealing (SA) and TS are employed. In the same area, CRO algorithm which inspired from the chemical reactions of molecules is developed and becoming popular in researchers to tackle the real life NP-hard problems (Lam, Li, and Yu, 2012; Truong, Li, and Xu, 2013). Recently, CRO has modified by incorporating several features from other metaheuristics such as SA and PSO and it is one of the most powerful search algorithms in solving mono-objective optimization problems (Bechikh et al. 2015; Lam and Li 2010). Therefore, we have employed the variant of CRO algorithm to solve our mathematical model.

5. Hybrid Chemical Reaction Optimization with Tabu search (CROTS)

CRO governs by the two laws of thermodynamics e.g. conservation of energy and entropy of the system always tends to increase. In Chemical reaction, unstable molecules attains the stable state when potential energy converts to the kinetic energy and molecules kinetic energy decreased steadily in the direction of the surroundings. The structural change in molecules is activated by the collision which occurs between the multiple molecules or molecules and the wall of the container. The molecules energy is manipulated by the different elementary reactions which triggered by the collision. Basically, CRO consist of four elementary reactions in which two reactions are unimolecular and remaining two are inter-molecular reactions. Moreover, on wall ineffective collision and Decomposition belongs to the category of unimolecular and inter-molecular ineffective collision and synthesis belongs to inter-molecular category. In unimolecular reactions, one molecule hit the wall of the container and may decompose into two molecules or remain single. In inter-molecular case, more than one molecules collide with each other and may form a single molecule or remain as previous. The intensification (local search) is carried out by the two ineffective collision reactions (on wall and inter molecular) and diversification handle by the decomposition and synthesis reactions. The global optima in the solution space will find out using the combination of intensification and diversification. Distribution of energy among the molecules and transfer of energy from one form to another are the most distinguishable features of the CRO.

The CRO is a variable population based EA and molecule is the basic manipulating agent. The various characteristics of the molecule are molecule structure (ω), potential energy (*PE*) and kinetic energy (*KE*). Molecule structure (ω) represents the solution of the problem. In this case molecule structure (ω) is the vector which consist of all the binary, continuous and integer decision variables. Potential energy gives the objective function value which corresponds to the molecule structure. The kinetic energy (*KE*) is the measure of tolerance of accepting the worst solutions than the previous one and its ability to jump out from the local minima. There are some other features which records the information when molecules undergoes collision. A Number of hits (*NumHit*) stores the molecules total number of moves (collisions). The Minimum structure (*Minstruct*) is the molecule structure corresponds to the minimum potential energy attained so far in populations. When molecule attains the *MinStruct*, the corresponding *PE* is the minimum potential energy (*MinPE*). Minimum Hit number (*MinHit*) represents the number of moves when a molecule realizes the Minimum structure (*Minstruct*).

Basically, CRO algorithm is implemented in three stages like any other metaheuristics i.e. initialization, iterations and termination. In the initialization phase, we set the different below mentioned parameters and initialize the algorithm. *PopSize* defines the molecules population size, *KELossRate* denotes the loss rate of kinetic energy in the elementary reactions, *MolColl* decides whether unimolecular and multi molecular reaction occurs. Also, the buffer, Initial *KE* and parameters α, β controls the intensification and diversification of the process. The pseudo code of this initialization phase is given in Fig. 3.

Algorithm 1"Molecule Initialisation"

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

Fig. 3. Pseudo code of molecule initialisation

The four operators (elementary reactions) are described as follows:

1. On wall ineffective collision: In this reaction molecule collides with the wall of the container and bounces back remaining as a single molecule. There will be very little change occurs in the molecule structure and potential energy. The new molecule structure $\omega^{'}$ is selected from the original molecule structure ω using the neighbourhood search operator. This change will happen only if

$$PE_{\omega} + KE_{\omega} \geq PE_{\omega'} \tag{14}$$

We get

$$KE_{\omega'} = \left(PE_{\omega} + KE_{\omega} - PE_{\omega'}\right) \times a \tag{15}$$

Where a is the random number in the interval of $\left[KELossRate,\ 1\right]$ and $(1-a)$ denotes the portion of KE lost to the surrounding environment when molecule hits the wall. Next, the remaining energy is stored into the central energy buffer which can be used for triggering the decomposition. If equation (14) does not satisfied then this collision is not allowed and an original molecule with same structure remains in the population without any change. The detailed steps are given in Fig. 4.

Algorithm 2 On wall Ineffective Collision $\left(M,\ \text{buffer}\right)$

1: **Input**: a molecule M with molecular structure ω *i.e.* M_{ω} and central energy buffer
2: Obtain the new molecule from neighboring approach, i.e. $\omega^{'} = N\left(\omega\right)$
3: Calculate the $PE_{\omega^{'}}$ *by* using $f(\omega^{'})$ i.e. $\text{PE}_{\omega^{'}} = f(\omega^{'})$
4: **if** $PE_{\omega} + KE_{\omega} \geq PE_{\omega'}$ **then**
5: *Get* a randomly in the interval $[KELossRate, 1]$
6: Set $KE_{\omega^{'}} = (PE_{\omega} - PE_{\omega^{'}} + KE_{\omega}) \times a$
7: Update $buffer = buffer\ +\ (PE_{\omega} - PE_{\omega^{'}} + KE_{\omega})\ \times\ \left(1-a\right)$
8: Update the profile of M by $\omega = \omega^{'}$, $PE_{\omega} = PE_{\omega^{'}}$ and $KE_{\omega} = KE_{\omega^{'}}$
9: **if** $PE_{\omega}\ <\ MinPE_{\omega}$ **then**
10: Update the $MinStruct_{\omega} = \omega$, $MinPE_{\omega} = PE_{\omega}$ and $MinHit_{\omega} = NumHit_{\omega}$
11: **end if**
12: **end if**
13: **Output**: M and buffer

Fig. 4. Pseudo code of on wall ineffective collision function

2. Decomposition**:** This reaction take place when single molecule hits the wall and decomposes into two or more (consider two only in this case) molecules. The new molecules structure must be very different from the original molecule structure. This reaction is useful for exploring the more search space after enough local search performed by on wall ineffective collision. To create the greater number of molecules more energy is needed and the process takes it from central energy buffer. Furthermore, the amount of energy to be withdrawn from buffer depends on two random numbers δ_1, δ_2 which uniformly generated in the range (0, 1).

The modified energy conservation condition of decomposition is as follows:

$$PE_{\omega} + KE_{\omega} + \delta_1 \times \delta_2 \times buffer \geq PE_{\omega_1^{'}} + PE_{\omega_2^{'}} \tag{16}$$

If this condition holds then the original molecule is converted into two molecules and energy involved is given by below equation.

$$E_{deco} = \left(PE_{\omega} + KE_{\omega} + \delta_1 \times \delta_2 \times buffer\right) - \left(PE_{\omega_1^{'}} + PE_{\omega_2^{'}}\right) \tag{17}$$

The transformation of remaining energy to newly generated molecules is provided by

$$KE_{\omega_1^{'}} = E_{deco} \times \delta_3 \tag{18}$$

$$KE_{\omega_2^{'}} = E_{deco} \times (1 - \delta_3) \tag{19}$$

Where δ_3 is a uniformly generated random number in the interval of (0, 1). The energy in central buffer is also updated as follows:

$$buffer' = \left(1 - \delta_1 \delta_2\right) buffer \tag{20}$$

The detailed flow of decomposition operator is given in Fig. 5.

Algorithm 3 Decompostion $(M,\ \text{buffer})$

1: **Input**: a molecule M *with molecular structure* ω *i.e.* M_ω and central energy buffer
2: Create $M_{\omega_1^{'}}$ and $M_{\omega_2^{'}}$
3: Obtain $\omega_1^{'}$ and $\omega_2^{'}$ from ω
4: Calculate $PE_{\omega_1^{'}} = f(\omega_1^{'})$ and $PE_{\omega_2^{'}} = f(\omega_2^{'})$
5: **if** $PE_\omega + KE_\omega \geq PE_{\omega_1^{'}} + PE_{\omega_2^{'}}$ **then**
6: Set $E_{dec} = PE_\omega + KE_\omega - PE_{\omega_1^{'}} - PE_{\omega_2^{'}}$
7: **go to** step 13
8: **else**
9: Generate $\delta_1, \delta_2 \in [0,1]$
10: Set $E_{dec} = PE_\omega + KE_\omega + \delta_1\delta_2 \times \text{buffer} - PE_{\omega_1^{'}} - PE_{\omega_2^{'}}$
11: **if** $E_{dec} \geq 0$ **then**
12: Obtain the buffer = buffer $\times$ $(1 - \delta_1\delta_2)$
13: Generate $\delta_3 \in [0,1]$
14: Set $KE_{\omega_1^{'}} = E_{dec} \times \delta_3$ and $KE_{\omega_2^{'}} = E_{dec} \times (1 - \delta_3)$
15: Update the $MinStruct_{\omega_1^{'}} = \omega_1^{'}$, and $MinStruct_{\omega_2^{'}} = \omega_2^{'}$
16: $MinPE_{\omega_1^{'}} = PE_{\omega_1^{'}}$ and $MinPE_{\omega_2^{'}} = PE_{\omega_2^{'}}$
17: Destroy M_ω
18: **else**
19: Destroy $M_{\omega_1^{'}}$ and $M_{\omega_2^{'}}$
20: **end if**
21: **end if**
22: **Output**: $M_{\omega_1^{'}}$ and $M_{\omega_2^{'}}$, buffer

Fig. 5. Pseudo code of decomposition operator

3. Inter-molecular ineffective collision: This reaction corresponds when multiple randomly selected molecules (assume two in this framework) collide with each other and bounces back away. There is no major change in the molecularity of the molecules before and after the collision because new molecules structure produces from original molecules neighbourhood structure. Moreover, it is similar to the on wall ineffective collision except no KE drawn to the buffer and multiple molecules.

The on wall and inter-molecular ineffective collision work as a local search operator in CRO. This collision takes place only if

$$PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} \geq PE_{\omega_1^{'}} + PE_{\omega_2^{'}} \tag{21}$$

The energy released is given by:

$$E_{inter} = \left(PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2}\right) - \left(PE_{\omega_1^{'}} + PE_{\omega_2^{'}}\right) \tag{22}$$

The remaining energy is distributed in two new molecules using random number δ_4 as follows:

$$KE_{\omega_1^{'}} = E_{inter} \times \delta_4 \tag{23}$$

$$KE_{\omega_2^{'}} = E_{inter} \times (1 - \delta_4) \tag{24}$$

The detailed flow of this reaction is given in Fig. 6.

Algorithm 4 Inter Molecular Ineffctive Collision $\left(M_{\omega_1} \text{and } M_{\omega_2}\right)$

```
Input: molecules M_ω1 and M_ω2
Obtain ω1' = N(ω1) and ω2' = N(ω2)
Calculate PE_ω1' = f(ω1') and PE_ω2' = f(ω2')
Set E_inter = (PE_ω1 + PE_ω2 + KE_ω1 + KE_ω2) - (PE_ω1' + PE_ω2')
if E_inter ≥ 0 then
    Generate δ4 ∈ [0,1]
    Calculate KE_ω1' = E_inter × δ4 and KE_ω2' = E_inter × (1 − δ4)
    Assign ω1 = N(ω1') and ω2 = N(ω2')
    Update PE_ω1 = PE_ω1' and PE_ω2 = PE_ω2'
    Update KE_ω1 = KE_ω1' and KE_ω2 = KE_ω2'
    if PE_ω1 < MinPE_ω1 then
        MinStruct_ω1 = ω1 and MinPE_ω1 = PE_ω1
    end if
    if PE_ω2 < MinPE_ω2 then
        MinStruct_ω2 = ω2 and MinPE_ω2 = PE_ω2
    end if
end if
Output: M_ω1' and M_ω2'
```

Fig. 6. Pseudo code of inter molecular ineffective collision function

4. Synthesis: During this reaction, multiple molecules (assume two in this framework) collide with each other and form a new molecule. This reaction is opposite of decomposition reaction and it happens when below criteria meet.

$$PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} \geq PE_{\omega_1^{'}} \tag{25}$$

The remaining energy is given by:

$$KE_{\omega'} = PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} - PE_{\omega'} \tag{26}$$

The newly generated molecule is having the better ability to explore the solution region very effectively because of higher kinetic energy. Thus, its help for diversification of solution space. The detailed steps of a synthesis reaction are given in Fig. 7.

Algorithm 5 Synthesis$\left(M_{\omega_1} \text{and } M_{\omega_2}\right)$

Input : molecules M_{ω_1} and M_{ω_2}
Obtain $\omega^{'} = N\left(\omega_1, \omega_2\right)$
Calculate $PE_{\omega^{'}} = f(\omega^{'})$
if $PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} \geq PE_{\omega^{'}}$ **then**
    Set $KE_{\omega^{'}} = (PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2})$ - $PE_{\omega^{'}}$
    Update $MinStruct_{\omega^{'}} = \omega^{'}$ and $MinPE_{\omega_1^{'}} = PE_{\omega^{'}}$
    Destroy M_{ω_1} and M_{ω_2}
else
    Destroy $M_{\omega^{'}}$
end if
Output: $M_{\omega^{'}}$

Fig. 7. Pseudo code of synthesis operator

In CRO, higher energy state molecule moves and collision take place. In each iteration, the uniformly generated random number *b* in the range (0, 1) decides the unimolecular or inter-molecular collision. Molecule undergoes the unimolecular collision if *b* > *MoleColl* and if *b* <= *MolColl* then inter-molecular collision. In a unimolecular collision, if (*NumHit* - *MinHit* > α) then decomposition take place, otherwise on wall ineffective collision triggers. Moreover, during an inter-molecular collision, if the kinetic energy of both the molecules is less than β then synthesis would happen, otherwise inter-molecular collision occurs. Algorithm evaluates the iteration best solution with the global best solution at the end of each iteration and if iteration best solution is superior to global best then stores in memory. This iteration will continue until the stopping criteria meet and once it meets then the algorithm will stop. The best solution value (i.e., Lowest total cost) will be outputted in the final stage of the algorithm.

In recent times, as explained earlier CRO has been efficiently implemented to solve the NP-hard problems such as QAP, RCPSP (Lam and Li 2010) and task scheduling in grid computing

(Xu, Lam, and Li 2011). In basic CRO, decomposition and synthesis reaction produces the molecules with very different structure, but the molecules produced after on wall and inter-molecular ineffective collisions are not too much different with the original molecules (Li and Pan 2013). It demonstrates that diversification (exploration) of the basic CRO performs well, but intensification (exploitation) needs to be improved using local search operator. Therefore, in this research, we have embedded the TS into CRO for improving the solution quality and convergence ability.

Basically, TS belongs to the category of the neighbourhood (local) search optimization techniques which start with the initial solution and exploration of the solution region is done by iteratively examining the neighbouring solutions of the current solution by simple local modifications. In order to prevent cycling of the solutions and searching of global optima, the recently developed solutions are stored in a list called Tabu list. Normally, on the basis of satisfaction of aspiration criteria the solutions from the tabu list can be selected. In this algorithm, we have taken CRO and merge with TS to solve the mathematical model. Therein, initially one out of four elementary reactions would take place and iteration best solution finds out. In the next step, the TS is employed for searching the neighbourhoods (local) solutions (S_n) of the iteration best solutions (S_c). The overall best solution is updated by comparing with neighbour best solutions ($S_{c'}$). The various parameters used in the TS are described as below: S_c= Current best solution, g = generation, $S_{c'}$ = Next best solution, S_n = Neighboring solutions of current best solution (S_c). The TS based local search along with the main steps is described in the next sub section.

5.1 TS-based local search

The detailed steps of TS based local search are as follows:

1) Compute the current best solution of CRO (S_c)
2) Perform the below steps until stopping criteria meet
3) Let g=0
4) Generate the S_n neighbouring solutions from the current best solution to construct a neighbour set.
5) Compute the each neighbouring solutions fitness values after evaluating each solution and set all the neighbouring solutions according to the non-decreasing order of the fitness values.
6) The following two rules are used for selecting the next best solution *($S_{c'}$).* i) Select the first solution which is not in the tabu list and ii) if all the solutions are in tabu list, then choose the first solution which satisfies the aspiration criteria. The simple aspiration criteria is used in this paper i.e., if the objective value of neighbouring solution is better than current best-known solution.
7) If the new current solution is better than the best solution, then update the best solution with a neighbour solution and update the tabu table list also.

The algorithm 6 illustrates the more details about TS-based local search which provided in Fig. 8.

Algorithm 6: TS-based local seacrh

```
Input: Molecules Best Solution (ω)
g =0
while (g < S_n) do
    Obatin ω' = N(ω)
    if ω' is non-tabu or satisfies the aspiration criteria (Evalute ω')
        if (fitness (ω') < fitness (ω)
            update the best solution (ω) with ω'
            update the tabu list(ω')
        end if
        g =g+1
    end if
end while
Output: Best Solution
```

Fig. 8. Pseudo code of TS based local search

5.2 The CROTS algorithm framework

The stepwise procedure of the proposed CROTS algorithm is given as follows:

Step 1: Assign the parameter values of the model

Step 2: Initialization stage

Step 2.1: Set the algorithmic control parameter values such as *PopSize*, *KELossRate*, *MolColl*, *buffer*, α, β , *KE*, *TabuLength* and *numNeighbour*.

Step 2.2: Create the *Popsize* number of molecules randomly in the solution space.

Step 3: Compute the *PE* value of each molecule in the population

Step 4: If the stopping criteria satisfy, output the best solution; otherwise, execute step 4.3 to 4.5.

Step 4.3: Get b randomly from [0, 1], if b > *MolColl* then execute sub-step 4.4, otherwise, execute sub-step 4.5.

Step 4.4: Select a molecule M_w from *PopSize* randomly and implement the on-wall ineffective collision or decomposition based on the decomposition criteria. The pictorial representation of this two collisions is shown in Fig. 9.

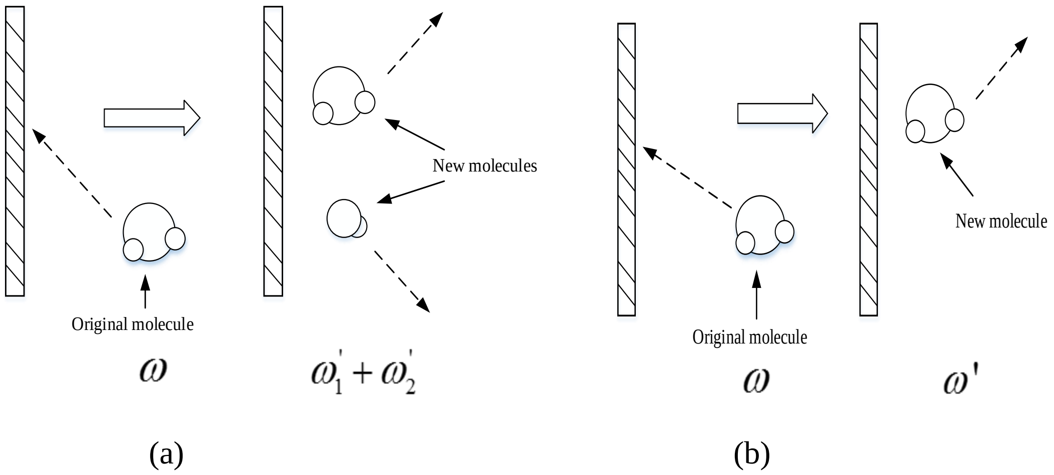

Fig. 9. Unimolecular collision: (a) On wall ineffective collision. (b) Decomposition

Step 4.5: Select two molecules randomly from *PopSize* and implement the inter-molecular ineffective collision or synthesis based on the synthesis criteria. The Fig. 10 portrays the two inter-molecular collisions.

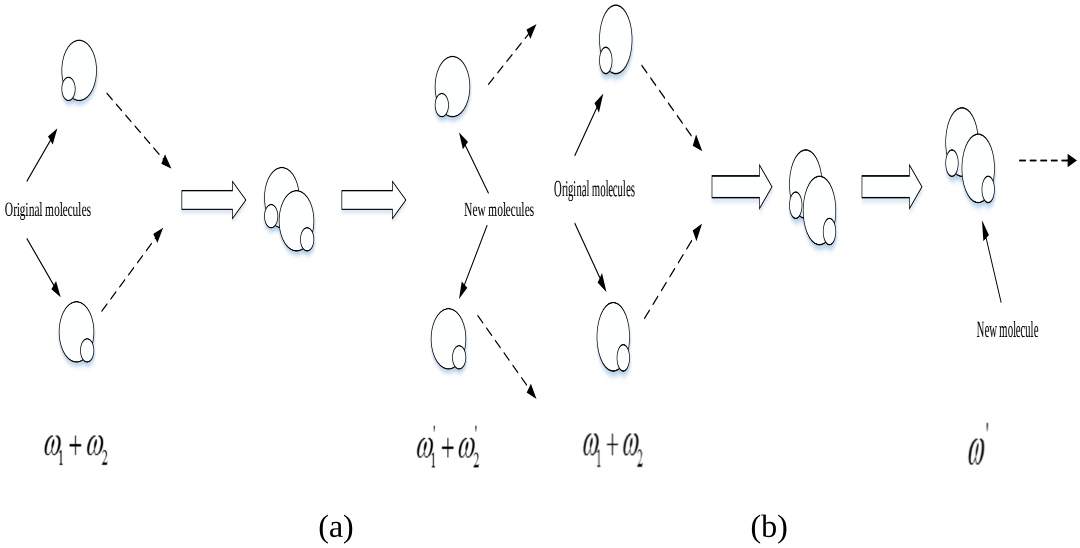

Fig. 10. Inter-molecular collision: (a) Inter-molecular ineffective collision. (b) Synthesis

Step 5: Compute the best solution from the population and execute the TS-based local search using algorithm 7 on the obtained best solution.

Step 6: Iteration continues and go back to Step 4.

The detailed steps (Pseudo code) of CROTS function are shown in Fig. 11.

Algorithm 7 CROTS

Input: Problem specific information includes objective function f, constaints and parameters values.
\\ Initialiation
Assign parameter values to $PopSize,\ KELossRate,\ MoleColl,\ buffer, InitialKE,\ \alpha\ and\ \beta$
Create Popualtion-size number of molecules using Algorithm 1
\\ Iterations
while the stopping criteria not satisfy **do**
  Get b randomly from $[0,1]$
  if $b > MoleColl$, **then**
    Select a one molecule M_{ω} from $PopSize$ randomly
    if Decompostion Criterion met **then**
      Perform Decompostion reaction using Algorithm 3
    else
      Perform on-wall ineffective collision using Algorithm 2
    end if
  else
    Select two molecules M_{ω_1} and M_{ω_2} from $PopSize$ randomly
    if Synthesis criterion met **then**
      Perform the Synthesis reaction using Algorithm 5
    else
      Perform the Inter molecular ineffective collision using Algorithm 4
    end if
  end if
  Search for the best solution in the population
  Perform a tabu search on the neighbours of the best solution and update the tabu table
end while
Output: the best solution of the final generation and its objective function value

Fig. 11. Pseudo code of CROTS function

The description of the proposed CROTS algorithm along with satisfaction criteria of all chemical reactions in the form of a flowchart is shown in Fig 12.

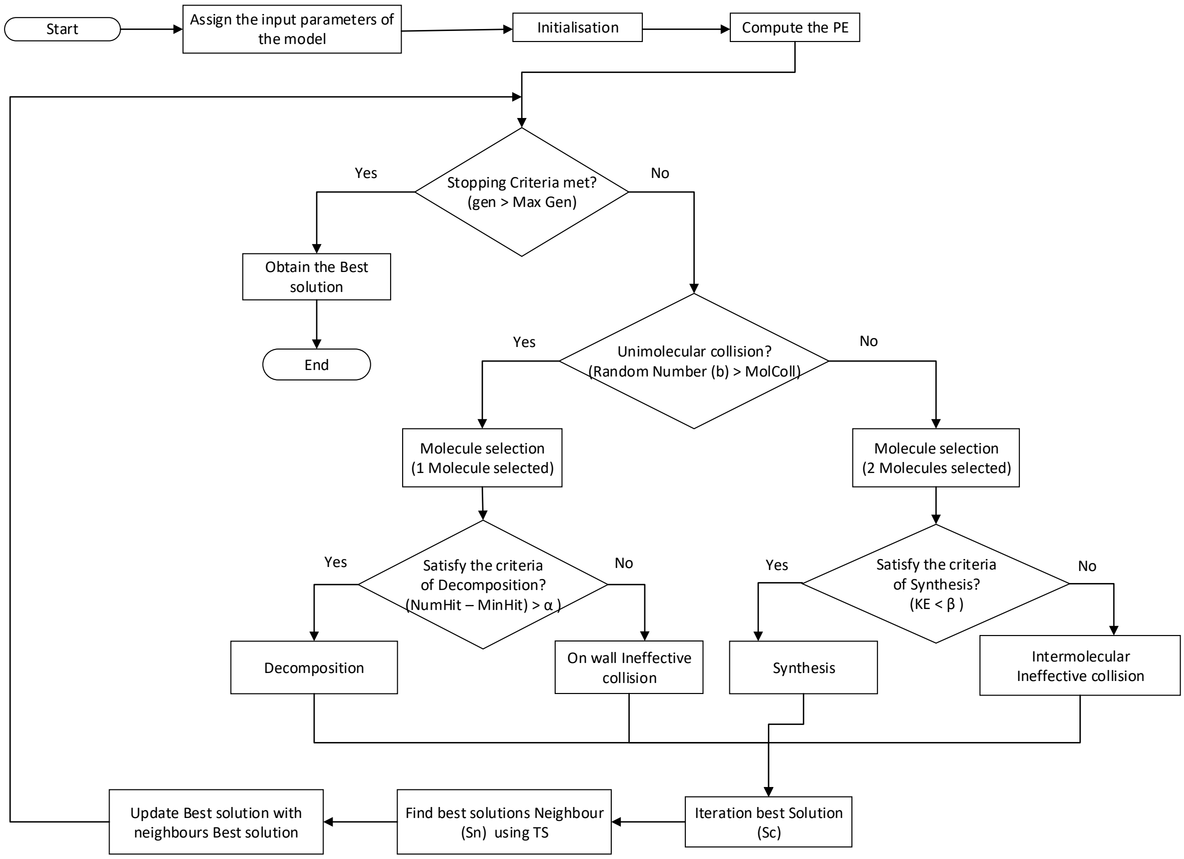

Fig 12. Flowchart of CROTS

6. Computational Results and Analysis

The performance of the proposed CROTS algorithm for solving the bulk wheat transportation and storage problem is evaluated through the computational experiments. The various data required for solving this MINLP model are taken from several secondary reliable sources such as annual reports of Food Corporation of India, ministry of railways, ministry of food processing, and CAG reports. Therein, the information related to locations of origin nodes, silos and destination nodes along with the quantity available, silo capacity and demand of destination nodes have been collected from FCI portal (http://fci.gov.in), CAG report 2013 and PDS Portal of India (http://pdsportal.nic.in/main.aspx). The vehicles related data such as capacity, cost and distances between nodes have been taken from the High Level Committee (HLC, 2015) report and Freight Operations Information System portal (https://www.fois.indianrail.gov.in) of ministry of railways, GOI. Furthermore, the inventory and operational cost related data of the model have been gathered from HLC 2015 report. The cost related parameter values have been reported in Table 1a. Furthermore, the summary of variations of vehicle related parameter values and demand, distances, quantity available along with silo capacity are given in Table 1b and 1c, respectively. Table 2 gives the description about ten cases of the problem which covers the major producing and consuming states movement in India. All the problem cases are classified into the three categories depending on the total number of nodes in the problem. The small case category consists of 20 nodes including origin, silos and destination nodes. The total nodes in the medium category vary from

21 to 50. Large scale category is considered from above the 50 total nodes. As per this classification, out of 10 cases, initial three cases are small case types, case 4 to 7 belongs to the category of medium scale and case 8 to 10 are large size problems. The problem case name is represented by the origin nodes, silos, destination nodes and time periods (months) i.e. (O-S-D-M). In this section, the CROTS and CRO algorithm are coded in MATLAB R2014a and all experiments are carried out on a personal computer with Intel Core i5, 2.90 GHz processor with 8 GB RAM in a Windows 7 environment. We have compared the performance of CROTS with the basic CRO algorithm.

Table 1a Depicting the various cost parameter values

Parameter	$s_{x_1}, s_{x_2}, s_{x_3}$	$q_{y_1}, q_{y_2}, q_{y_3}$	$f_{z_1}, f_{z_2}, f_{z_3}$	c_{ij}^{α}	c_{jk}^{β}	c_{jk}^{α}	w_j	V_j
Values (INR)	200, 150, 100	1000, 700, 500	300, 250, 200	20	15	20	100	50

Table 1b Summary of variations of vehicle related data

Parameters	$v_i^{x_1 t}$	$v_i^{x_2 t}$	$v_i^{x_3 t}$	$l_j^{y_1 t}$	$l_j^{y_2 t}$	$l_j^{y_3 t}$	$h_j^{z_1 t}$	$h_j^{z_2 t}$	$h_j^{z_3 t}$
Values	500 - 1000	600 - 1100	700 - 1200	6 - 15	8 - 18	9 - 20	300 - 500	400 - 600	500 - 700

Table 1c Summary of variations of demand, distances, quantity and silo capacity

Parameters	D_k^t	d_{ij}^{α}	d_{jk}^{β}	d_{jk}^{α}	Q_i^t	R_j
Values	15000 - 30000	10 -50	400 – 800	300 - 700	20000 - 45000	50000 - 200000

Table 2 Description of considered problem cases

Problem Size	Case Type (O-S-D-M)	Origin nodes	Silos	Destination nodes	Time periods (Months)
Small size	Case 1 (3-2-3-2)	3	2	3	2
	Case 2 (5-3-5-3)	5	3	5	3
	Case 3 (8-5-6-2)	8	5	6	2
Medium Size	Case 4 (13-6-11-3)	13	6	11	3
	Case 5 (15-9-12-2)	15	9	12	2
	Case 6 (18-9-17-2)	18	9	17	2
	Case 7 (20-10-15-3)	20	10	15	3
Large size	Case 8 (25-12-26-2)	25	12	26	2
	Case 9 (40-25-35-3)	40	25	35	3
	Case 10 (50-35-60-3)	50	35	60	3

The parameter tuning of any metaheuristics is a very important part because it mostly affects the solution quality of the algorithm. According to Lam and Li (2010), there are no theoretical guidelines available for parameter tuning of metaheuristics. The adjustments rely on the experience and preferences of researchers. The different parameters of proposed CROTS such as PopSize, KELossRate, Tabu length etc. are mentioned in Table 2. At the beginning, the initial combination of the parameter has been determined by running the CROTS algorithm with random parameter values for a few times. Next, on the basis of the initial parameter, we investigate the parameter one at a time by varying their values and keeping the remaining values as in the initial combination. For chosen value of each parameter, we run the algorithm 30 times and the smallest mean total cost is computed by comparing the mean of the 30 runs among the chosen values. All the tuned parameter values are reported in Table 3. Furthermore, all the experiments are performed over the 20 runs and termination criteria is set as maximum generation of 1500 in each run.

Table 3 Parameter values for all cases

Parameters	CRO	CROTS
popsize	300	300
KElossRate	0.2	0.2
intialKE	40.36×10^6	40.36×10^6
Molecoll	0.3	0.3
alpha	3	3
beta	40.34×10^6	40.34×10^6
Tabu length	-	15
numNeighbour	-	50

The computational results along with the total no of constraints and variables for each case are reported in Table 4. The best and worst solutions are obtained after 20 runs of each algorithm. As we can see from Table 4, the CROTS yields the better performance with less computational time compared with CRO in each case type. Furthermore, the standard deviation of CROTS algorithm is also less compared with basic CRO in all cases. The mean of total cost obtained through CROTS is smaller than CRO algorithm. This demonstrates that the CROTS is more robust than the CRO algorithm. In all the ten cases of the problem, hybrid CROTS algorithm outperformed the basic CRO algorithm. This overall result of the ten cases illustrates that CROTS algorithm is more efficient and effective than CRO algorithm for solving this types of problems.

Table 4 Computational results of ten cases

Problem Size	Case Type	Algorithm	Best Solution	Worst Solution	Mean	Standard Deviation	Computational time (s)	No of constraints	No of Variables
Small Size	Case 1 (3-2-3-2)	CRO	1.63×10^9	1.83×10^9	1.72×10^9	67140173	6.1464	1094	196
		CROTS	1.56×10^9	1.77×10^9	1.66×10^9	60116465	5.3784		
	Case 2 (5-3-5-3)	CRO	3.00×10^9	3.25×10^9	3.16×10^9	55667448	7.3008	6660	729
		CROTS	2.96×10^9	3.17×10^9	3.10×10^9	52728761	6.1076		
	Case 3 (8-5-6-2)	CRO	2.66×10^9	2.91×10^9	2.80×10^9	96803582	15.2101	14074	1070
		CROTS	2.49×10^9	2.81×10^9	2.68×10^9	92123434	12.3345		
Medium Size	Case 4 (13-6-11-3)	CRO	5.58×10^9	5.76×10^9	5.68×10^9	52296236	27.659	75045	3366
		CROTS	5.54×10^9	5.73×10^9	5.63×10^9	51540762	23.3034		
	Case 5 (15-9-12-2)	CRO	4.30×10^9	4.61×10^9	4.53×10^9	89921491	19.3129	94350	3744
		CROTS	4.18×10^9	4.50×10^9	4.41×10^9	88676617	15.8621		
	Case 6 (18-9-17-2)	CRO	6.10×10^9	6.31×10^9	6.20×10^9	59163681	28.7978	160234	5004
		CROTS	6.04×10^9	6.22×10^9	6.13×10^9	55634394	23.374		
	Case 7	CRO	1.75×10^{10}	2.04×10^{10}	1.94×10^{10}	752078719	35.9894	261765	7980
		CROTS	1.73×10^{10}	1.97×10^{10}	1.91×10^{10}	688477557	27.0862		

	(20-10-15-3)								
Large Size	Case 8 (25-12-26-2)	CRO	7.62×10^{9}	8.00×10^{9}	7.83×10^{9}	101673347	46.2075	453296	9888
		CROTS	7.44×10^{9}	7.82×10^{9}	7.68×10^{9}	97506312	35.2527		
	Case 9 (40-25-35-3)	CRO	3.71×10^{10}	4.01×10^{10}	3.86×10^{10}	890732557	342.0166	3048345	43950
		CROTS	3.67×10^{10}	3.98×10^{10}	3.80×10^{10}	883877197	250.4573		
	Case 10 (50-35-60-3)	CRO	8.04×10^{10}	8.36×10^{10}	8.17×10^{10}	920550638	983.0871	9142305	95655
		CROTS	7.90×10^{10}	8.23×10^{10}	8.11×10^{10}	890566975	830.0624		

The aggregated sample values of the decision variables for selected four cases have been reported in Table 5. The decision variables values such as total quantity transported from all origin nodes to all silos, from all silos to all destination nodes using rail and road, total number of each types of inbound trucks, rakes and outbound trucks used in all time periods and inventory available at the end of the period can get from this table. Moreover, the detailed structure of the case 1 has been represented on the supply chain network flow diagram in Fig. 13. In order to not confound the figure, the results of the second time period is not shown. The solid arrow indicates that the food grain is transported through road on that particular arc and dotted arrow denotes the rail transportation. The upper side value of the arc denotes the quantity transported and lower side indicates the different capacitated vehicles used on that arc. It can be observed from the Table 5 and Fig.13 that more quantity of food grain is transported through rail from silo to destination nodes compared to road transportation. The long distances, large volume of food grain quantity and low transportation cost are some of the reasons behind this.

Table 5 Sample aggregated decision variables values

	Case types			
Decision Variables	Case 2 (5-3-5-3)	Case 4 (13-6-11-3)	Case 6 (18-9-17-2)	Case 8 (25-12-26-2)
$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} a_{ij}^{\alpha t}$	284843	745665	1030300	1649225
$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} m_{jk}^{\beta t}$	144587	305680	507885	701700
$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} b_{jk}^{\alpha t}$	94595	194010	249200	453308
$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} r_{ij}^{x_1 t}$	5862	14002	19785	31115
$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} r_{ij}^{x_2 t}$	5245	14130	19200	31210
$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} r_{ij}^{x_3 t}$	4880	14086	19267	31010
$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} n_{jk}^{y_1 t}$	24	51	76	125
$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} n_{jk}^{y_2 t}$	22	49	83	109

$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} n_{jk}^{y_3 t}$	22	43	87	87
$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} n_{jk}^{z_1 t}$	1273	2700	3284	5940
$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} n_{jk}^{z_2 t}$	1285	2520	3369	6126
$\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} n_{jk}^{z_3 t}$	1214	2501	3323	6098
$\sum_{j\in J}\sum_{t\in T} B_j^t$	45661	245975	273215	494217

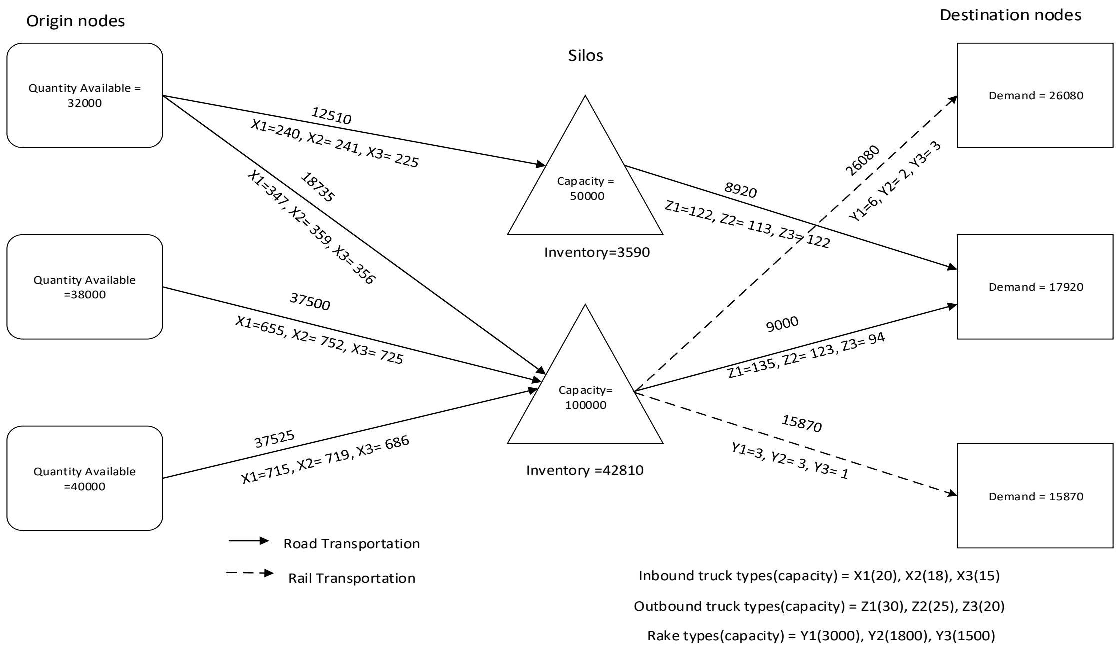

Fig 13. Two stage supply chain network with related decision variables for case 1

The graphical representation of 20 runs of each algorithm for selected four cases are shown in the Figs. 14 - 17. It is observed that the CROTS algorithm obtained the lowest cost in each run compared with original CRO algorithm.

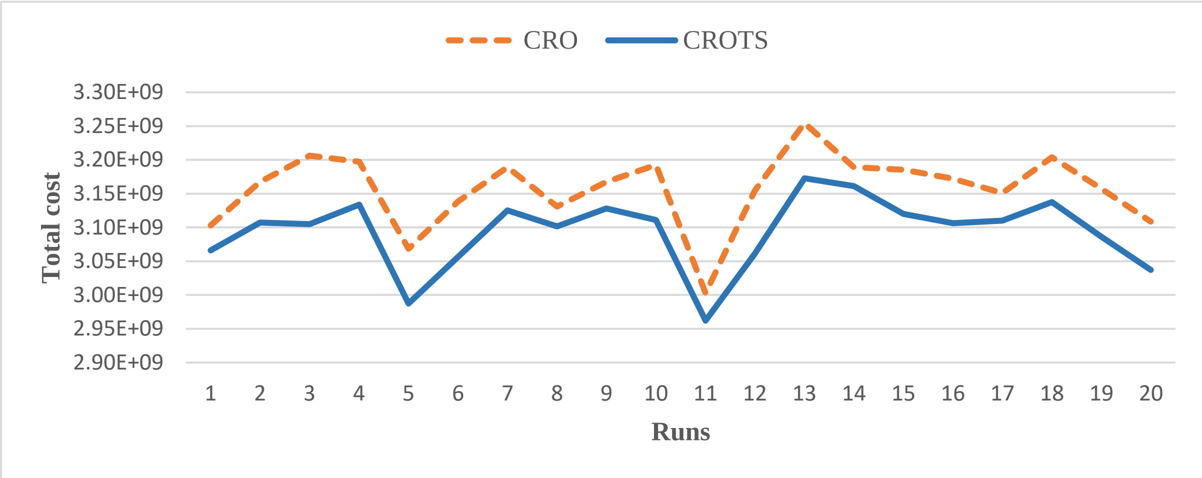

Fig. 14. Results of 20 runs of case 2

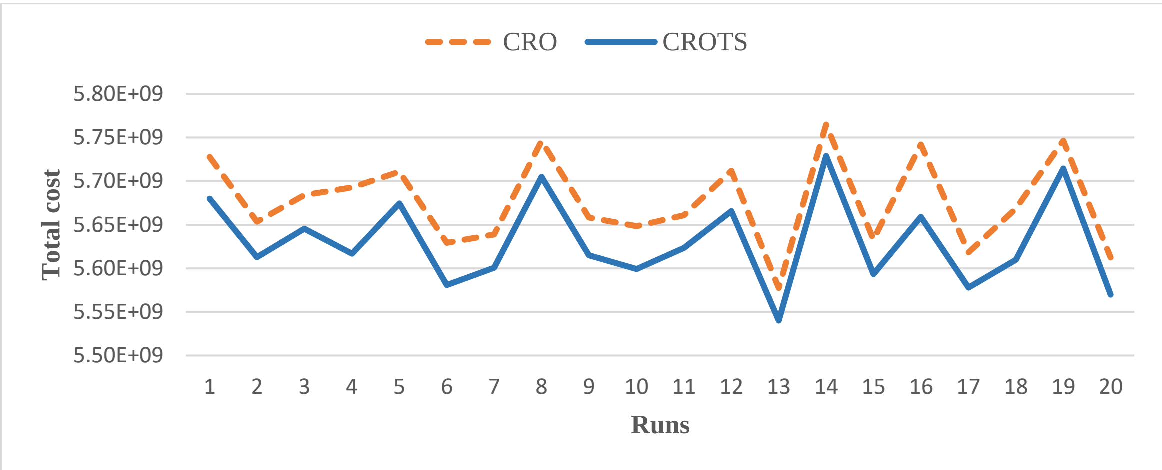

Fig. 15. Results of 20 runs of case 4

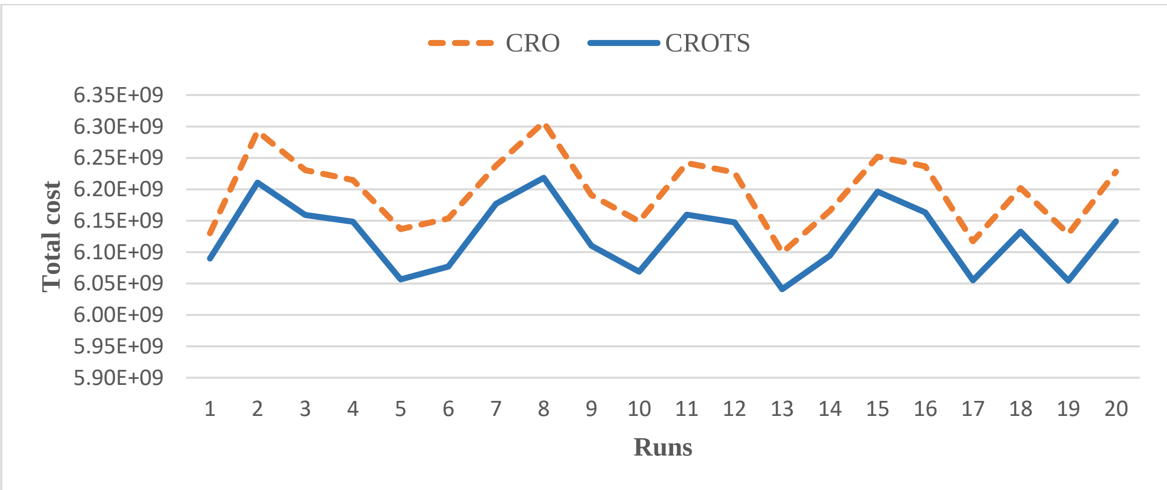

Fig. 16. Results of 20 runs of case 6

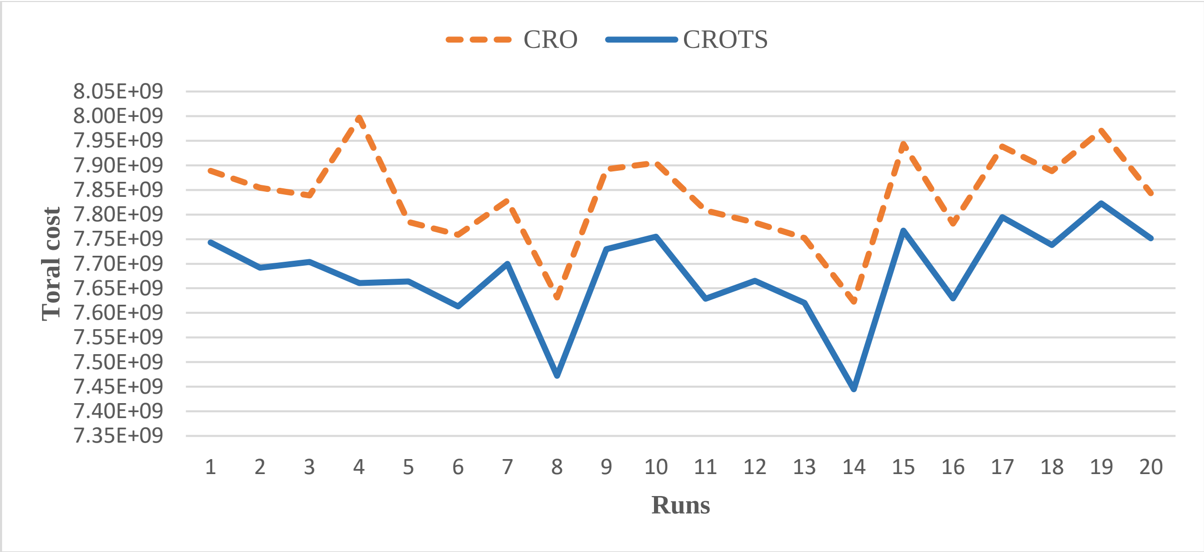

Fig. 17. Results of 20 runs of case 8

The convergence graphs of some of the runs of both the algorithms for chosen four case types are shown in the Figs. 18 - 21, where the CROTS algorithm converges faster than CRO algorithm in each case.

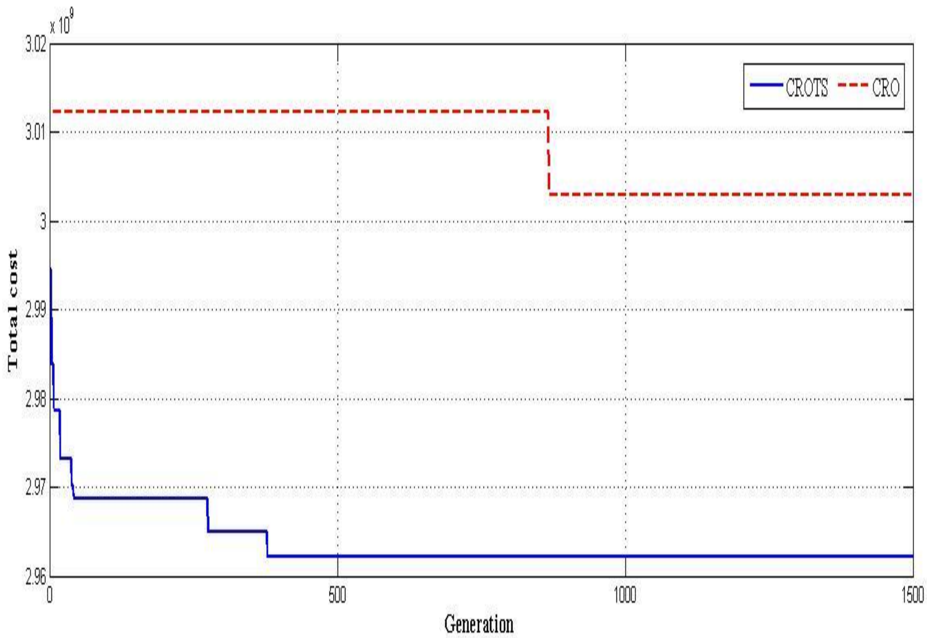

Fig. 18. Convergence graph of case 2

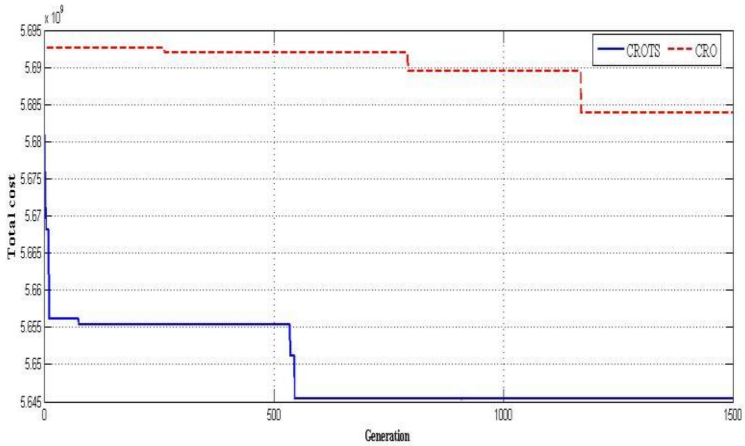

Fig. 19. Convergence graph of case 4

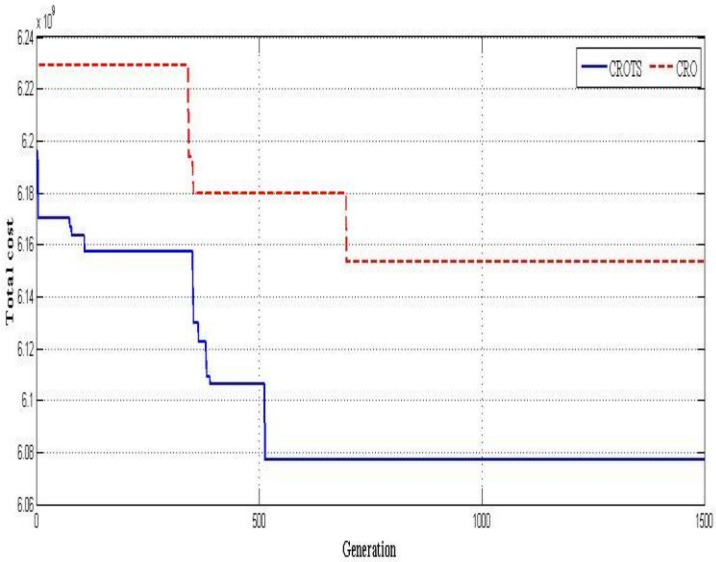

Fig. 20. Convergence graph of case 6

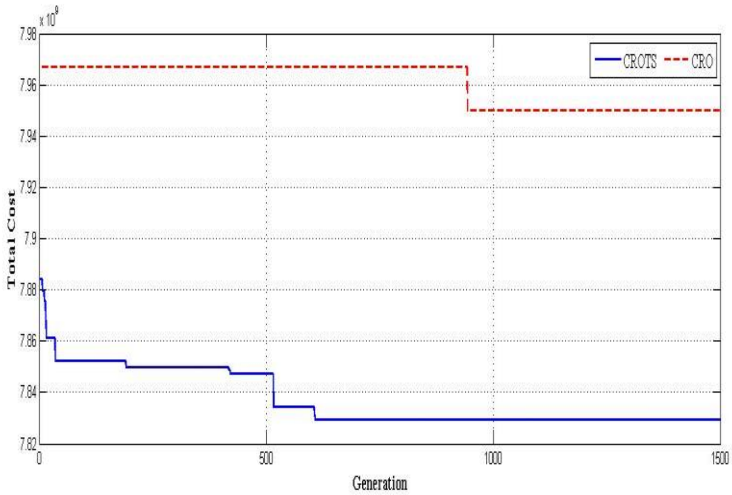

Fig. 21. Convergence graph of case 8

The conventional method of transportation and storage of food grain through gunny bags incurred the very high redundant cost of gunny bags and loading and unloading cost of gunny bags. According to the CAG 2013 report, FCI incurred an expenditure of INR 13.14 crore towards the cost of gunnies, stitching and handling charges, etc., during Rabi Marketing Seasons 2008-09 to 2011-12 in Punjab and Haryana states. The cost of gunny bags for transporting the 1 MT food grain is the INR 767.20. In addition, the loading and unloading time of the gunny bags from the vehicles is very large compared with little time in bulk food grains because of automation. The bulk food grain transportation and storage strategy can easily save this gunny bag and loading and unloading cost.

6.1 Statistical analysis of algorithms

The statistical analysis of the algorithms with a 95% confidence for the instances of selected four cases is carried out in this section using independent two-sample *t*-test to confirm the results. Generally, this is a hypothesis test for comparing the means of CROTS and CRO algorithm and two hypotheses are set as follows:

$$H_0 : \mu_{\text{CROTS}} \geq \mu_{\text{CRO}}$$

$$H_a : \mu_{\text{CROTS}} < \mu_{\text{CRO}}$$

Where, μ_{CROTS} and μ_{CRO} represents the means of the objective function values of CROTS and CRO algorithm respectively. The results of the *t*-test of chosen four cases are shown in Table 6.

Table 6 The ANOVA result of four cases

Problem size	Approach	N	Mean	SD	SE-Mean	T value	P value
5-3-5-3	CROTS	20	3.10×10^9	52728761	11790509	-3.688	0.000351
	CRO	20	3.16×10^9	55667448	12447620		
13-6-11-3	CROTS	20	5.63×10^9	51540762	11524865	-2.779	0.004209
	CRO	20	5.68×10^9	52296236	11693794		
18-9-17-2	CROTS	20	6.13×10^9	55634394	12440229	-3.941	0.000168
	CRO	20	6.20×10^9	59163681	13229401		
25-12-26-2	CROTS	20	7.68×10^9	97506312	21803074	-5.031	0.00001
	CRO	20	7.83×10^9	101673347	22734852		

The P values for all the cases in Table 6 are less than the commonly chosen value of 0.05 levels, so it proves that the mean total cost obtained through CROTS algorithm is less than mean total cost obtained using CRO algorithm. This statistical result confirms that CROTS algorithm gives the superior performance than the CRO algorithm.

7. Conclusion and Future Works

In this paper, the two stage multi-period bulk wheat transportation and storage problem of Indian food grain supply chain was investigated. The problem was formulated as an MINLP, where the objective function is to minimize the transportation, inventory and operational cost of wheat inside the silos. The novel hybrid CROTS algorithm which is the combination of CRO and TS has been proposed for addressing this problem. The TS was used as a local search operator to improve the performance of the CRO by increasing the diversification and intensification. The small, medium and large-scale problems sizes are solved using the proposed CROTS and CRO algorithm. The results of the CROTS algorithm have been compared with a CRO algorithm in computational results and analysis section. Therein, CROTS gives the superior performance in less computational time than the CRO algorithm for all problem sizes. Moreover, it is statistically confirmed that CROTS algorithm significantly gives the better result than CRO algorithm.

In future, we can extend this model to the probabilistic environment which takes cares of stochastic demand and procurement. Also, in order to improve the performance of the algorithm, there can be the detailed study of the parameter values and implementation strategy of the elementary reaction. In the present study, we have focused only on single food grain, but in near future, we can focus on multi-food grain transportation problem. Furthermore, this algorithm can be extended to solve the multi-objective optimization problems and scheduling problems. The insights obtained from this research would be helpful for the FCI to make the proper planning and coordination decisions among all the entities of food grain supply chain. The key decisions includes inventory planning, vehicle scheduling, optimal utilization of resources and reduction of wastages to minimize the total cost.

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