Grain silo location-allocation problem with dwell time for optimization of food grain supply chain network

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Abstract:

In the last few decades, production and procurement of food grain in India have steadily increased, however, storage capacity has not increased proportionally. The government of India (GOI) is establishing the various capacitated silos across the country to bridge this storage capacity gap. This paper presents a novel integrated multi-objective, multi-modal and multi-period mathematical model for grain silo location-allocation problem with Dwell time to support the decision-making process of GOI. Two conflicting objectives- minimization of total supply chain network cost and total lead time (transit and dwell time) are simultaneously optimized using two Pareto based multi-objective algorithms with calibrated parameters.

Keywords: Facility location-allocation problem, Multi-objective optimization, Mixed integer non-linear programming, Food grain supply chain, Non-dominated sorting chemical reaction optimization (NCRO)

1. Introduction

The continuously increasing population of India and the implementation of the National Food Security Act (NFSA) 2013 across the country cause the growing demand for food grain including wheat and rice. In order to meet this growing demand for food grain, the Government of India (GOI) is trying to increase the food grain production, procurement and reduce the post-harvest losses. In the past few decades, most of the developing countries have given greater emphasis on increasing production of food grain rather than reducing losses. Due to inadequate infrastructure and highly inefficient supply chain, the annual loss of food in India is near about 30-35% of the total production (Parwez, 2014). Storage and transit losses of food grain can be curbed through bulk storage and transportation instead of the conventional method of gunny bags. Therefore, GOI is moving towards the modernized food grain supply chain system which consists of bulk grain handling, transportation and storage facilities.

The Public Distribution System (PDS) is an Indian food security system which distributes the subsidized food grain to weaker and vulnerable section of the society. The major food grain supply chain related activities such as procurement from farmers in surplus states, storage, movement and distribution to deficit states are taken care by Food Corporation of India (FCI). In surplus states, food grain is procured from farmers by FCI and various State Government Agencies (SGAs) and stored in central warehouses. Wheat is procured in Rabi season (April to June) and rice in Kharif season (October to February). Further, food grain is allocated to the various deficit states on the basis of their demand and offtakes in the previous period. Then, deficit states handle the process of distribution of food grain to the final consumers through Fair Price Shops (FPS). Generally, intrastate and interstate food grain transportation are carried out by road and rail mode, respectively. The above described overall scenario of the Indian food grain supply chain is depicted in Fig. 1.

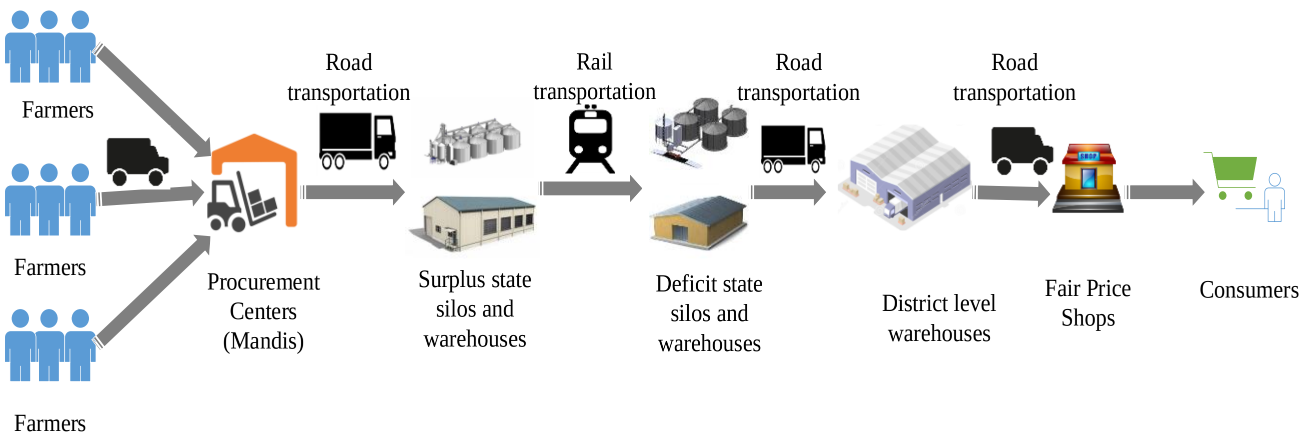


Fig. 1. The configuration of Indian food grain supply chain

The Comptroller and Auditor General of India, (CAG) 2013, report indicates that the storage capacity of the FCI has remained almost constant (15.2–15.6 Million Metric Ton (MMT)) during 2006-07 to 2011-12, whereas the central pool stock steadily increased from 21 MMT in 2007 to 66.8 MMT in 2012 excluding the decentralized state's procurement. The storage gap in FCI against the required capacity has steadily increased from 5.995 MMT during 2007-2008 to 33.185 MMT in 2011-12 as represented in Fig. 2. This numerical data shows the mismatch between procured food grains quantity and available storage capacity. Thus, more storage capacity is needed to cope up with growing procurement. Furthermore, the sudden increase in the stock of food grains in the central pool raises the issue of a large quantity of food grain movement from surplus states to deficit states. To meet the shortfall in storage capacity, GOI has started constructing the various capacitated steel silos in procuring (base silos) and consuming states (field silos).

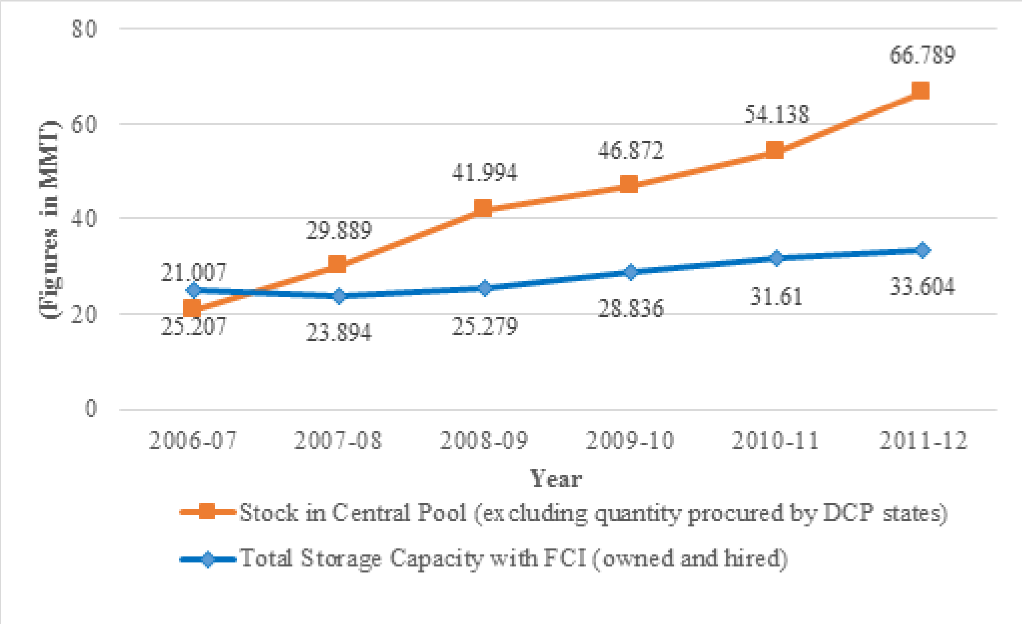


Fig. 2. Gap in Storage Capacity with FCI (Source: CAG 2013 report)

The main contributions of this paper are as follows. First, motivated by the above delineated real-life scenario of Indian food grain supply chain, a novel integrated multi-objective, multi-modal and multi-period mixed integer non-linear programming (MINLP) model is developed to solve the grain silo location-allocation problem of four echelon supply chain network. The mathematical model aims to minimize the two conflicting objective functions consisting of total food grain supply chain network cost and total lead time along with Dwell time (DT). The first objective function comprises of transportation cost (transportation cost from procurement centres to base silos, base silos to field silos and field silos to demand points), the fixed cost of silo establishment (base and field silo) and inventory cost at base and field silos. The second objective function involves dwell time (dwell time from procurement centres to base silos) and lead time (lead time from procurement centres to base silos, base silos to field silos and field silos to demand points). Specifically, the developed model concurrently optimizes the various critical decisions like location, allocation, capacity, inventory and transportation decisions. Second, the proposed model simultaneously considers the different realistic and practical features of the problem such as dwell time, multi-period, heterogeneous capacitated vehicles and their limited availability at each echelon, multiple sourcing, multi-modal transportation, geographically dispersed surplus and deficit states, capacitated base and field silos, and vehicle capacity constraints, etc. The waiting time of food grain stock at SGA warehouses must be reduced to avoid - deterioration of food grain quality, an increase of carry-over charges and food grain losses. Therefore, the new DT function is introduced for calculating the waiting time of food grain at procurement centers with the consideration of administrative activities, vehicles used for shipment between procurement centers and base silos and availability of base silos storage capacity. Third, to provide the compromise solution to the FCI and GOI, the model is solved using the recently developed multi-objective evolutionary algorithm called non-dominated chemical reaction optimization (NCRO) algorithm and compared the results with the well-known non-dominated sorting genetic algorithm (NSGA-II). Even though the NCRO algorithm is not original, to the best of our knowledge, it has not been used for any practical problems. Therefore, we feel that the application of the NCRO algorithm with calibrated parameters to solve a grain silo location-allocation problem and the comparison between NCRO and NSGA-II results for this problem can be one of the contributions. Finally, sensitivity analysis is conducted considering the eight parameters to obtain the managerial insights and practical implications for the effective decision-making process of food grain supply chain.

The rest of the paper is structured in the following manner. Section 2 provides the comprehensive review of the relevant existing literature. The problem delineation is given in Section 3. Section 4 illustrates the mathematical model of the problem including assumptions and notations. Section 5 deals with solution methodologies used for solving the model. Section 6 reports and discusses the computational results. Finally, the conclusion and some future extensions are given in Section 7.

2. Background and prior related work

The limited literature is available on multi-objective facility location-allocation or supply chain network design problem in the context of food supply chain. The previous relevant studies are divided into two sub-sections for better understanding. The first sub-section is dedicated to facility location-allocation and other relevant problems. The multi-objective optimization along with review papers in the field of food supply chain are described in second sub-section.

2.1 Facility location-allocation problems

Recently, Gholamian and Taghanzadeh, (2017) investigated the integrated supply chain network design problem of wheat and its products in Iran by simultaneously considering the long-term and mid-term decisions. They have incorporated various aspects like different types of wheat, flour factories, supplier selection, import of wheat and export of wheat products in the model. The novel features including waiting time, lead time, number of vehicles used for transportation, assignment decisions and scenario of producing and consuming states with various types of capacitated silos are considered in our current study. Etemadnia et al., (2015) addressed the hub location problem of fruit and vegetable supply chain system by considering the bimodal food transportation system. The objective function of the model was to minimize the transportation and hub location cost. Various transportation and total silo construction costs have been taken into account by Corner and Foulds, (2004) while developing a silo location model for sustainable grain supply chain. Therein, total construction cost was comprised of fixed and variable costs of silo establishment. The practical case of wheat logistical management problem focusing on storage and transportation system in Iran was addressed by Asgari et al., (2013). The novel warehouse preference constraints were included in their linear integer programing model. However, the main focus of the paper was on storage and transportation problem, not on the facility location-allocation problem. A two-stage food grain transportation model was developed by Maiyar and Thakkar, (2017) for the optimization of tactical and operational level decisions. However, they have not introduced the strategic, allocation, inventory, heterogeneous vehicles and multi-period characteristics in their paper.

Furthermore, Ge et al., (2015) developed the analytic and simulation models for minimization of handling cost of the wheat supply chain in the Canadian grain industry. Their goal was to find out the effective quality testing strategies to mitigate the contamination risks under the new trust-based declaration system of wheat segregation. Nourbakhsh et al., (2016) proposed the mathematical model for the minimization of total system cost which comprises of infrastructure investment and monetary value of post-harvest losses. The formulated model optimizes the number and location of drying facilities, transportation routing, transhipments between roadway as well as railway, and transportation infrastructure capacity expansion. The model has been tested using the case study of the real-world network in the state of Illinois. The food quality was incorporated in the multi-period production and distribution planning problem of two-stage network (Rong et al., 2011). They have developed the mixed integer linear programming (MILP) model which minimizes the total costs including production, transportation, inventory and waste disposal along with the cooling cost of transportation equipment and storage facilities.

The sugar cane loading station location problem in Thailand was investigated by Khamjan et al., (2013) and the mathematical model was solved by using the heuristic algorithm to minimize the investment, transportation and cane yield loss cost. The multi-modal, shipment quantity, inventory, lead time and waiting time characteristics are not considered in their model. The dynamic dairy facility location and supply chain planning problem with traffic congestion and uncertain demand was discussed by Jouzdani et al., (2013) using the empirical real-world case study of Tehran. The mathematical model aims to minimize the facility location cost, traffic congestion cost and raw/processed milk and dairy products transportation cost. Eskigun et al., (2005) considered the transit time, location of distribution centres and transportation mode while addressing the outbound supply chain network design problem. The transportation and lead time cost were the two main components of the objective function. Three mathematical models of grain transportation were presented for the determination of time, aggregate cost and rail network capacity (Hyland et al., 2016). Their main goal was to compare the conventional service of transportation with country elevators against shuttle service with terminal elevators. Furthermore, Rancourt et al., (2015) solved the food aid distribution problem of the Garissa region in Kenya by combining the need assessment and population data using mathematical programming methodology for the development of humanitarian logistics support decision tools. They have presented three location models for the design of last-mile food aid distribution network with the objective functions of minimization of social welfare cost, maximization of need coverage and minimization of required number of distribution centre locations. Boujelben et al., (2016) worked on multi-period facility location problem with numerous operational constraints and presented the MILP model. Initially, the authors have determined the transportation routes and costs from distribution centres to customers by means of dynamic clustering method and then solved the proposed model using commercial solver.

2.2 Multi-objective optimization in food supply chain

In recent times, An and Ouyang, (2016) developed a bi-level robust optimization model for profit maximization and post-harvest loss minimization of a food company by considering farmers, storage facilities and export markets. They have integrated the market equilibrium among farmers, stochastic crop yields and post-harvest loss in the developed bi-level

Stackelberg leader-follower game. A multi-objective, multi-period and multi-modal sustainable load planning problem has been studied by Baykasoğlu and Subulan, (2016) considering load allocation, outsourcing and transportation mode selection decisions. The main focus of their paper was on load planning problem of the intermodal transportation network with three objectives - minimization of overall cost, total transit time and total carbon emission. Bortolini et al., (2016) dealt with the tactical optimization problem of fresh food distribution network concentrating on operating costs, carbon footprint and delivery time objectives. The linear programming model was developed by them considering producers and retailers along with constraints of food quality dependence, market demand and production capacity of farmers. Additionally, Cardona-Valdés et al., (2014) simultaneously minimized the cost and travelling time of the two-echelon bi-objective stochastic problem by considering the demand uncertainty at the distribution centre. In the domain of meat supply chain network design, Mohammed and Wang, (2017a) developed three objective model to minimize the transportation cost, required transportation vehicles and delivery time. Later, the same authors have extended the model by considering the minimization of transportation cost, environmental impact, distribution time and maximization of average delivery rate (Mohammed and Wang, 2017b). They have suggested that the developed model can be expanded to the multi-period, multi-echelon scenario and solved using the multi-objective metaheuristic algorithms.

Moreover, two conflicting objectives comprising of the total cost and CO_2 emission were simultaneously optimized while solving the capacitated facility location-allocation problem (Harris et al., 2014), beef logistics network problem (Soysal et al., 2014) and milk distribution problem (Validi et al., 2014). Therein, Harris et al., (2014) considered the flexibility at the allocation level while dealing with the single source facility location problem and proposed the novel solution approach by integrating a multi-objective evolutionary algorithm with Lagrangian Relaxation. The transportation emission (due to distance, road condition, fuel types and weight of vehicles), return hauls and product perishability were concurrently considered by Soysal et al., (2014) in beef logistics network problem. Validi et al., (2014) developed the sustainable multi-objective model for the design of a capacitated distribution network of two-layer Irish dairy market supply chain. A fuzzy multi-objective linear programming model was presented for integrated supply chain network design of an edible vegetable oil producer which concurrently minimize the movement cost between suppliers and silos and manufacturer and warehouses (Paksoy et al., 2012). The mixed integer programming (MIP) model was proposed and solved with real-world case data from the Marmara region of Turkey for optimization of intermodal transportation network (Resat and Turkay, 2015). They included different transportation modes and time dependency on intermodal transportation in their model. A review of various operational research models employed in the domain of fresh fruit supply chain can be seen in Soto-Silva et al., (2016). In addition, Melo et al., (2009) critically analyzed the literature of facility location models for strategic decisions in the context of supply chain management, performance measures and optimization techniques. The comprehensive review of multi-criteria location problems focusing on bi-objective, multi-objective and multi-characteristic problems and their solution approaches was given by Farahani et al., (2010). A summary of the relevant studies on multi-objective optimization in the food supply chain indicating key features and the position of the current work in comparison with them have been included in Table 1.

Table 1 A summary of relevant studies on multi-objective optimization in food supply chain

Study	Single/ Multi period	Single/ Multi-modal	Echelons in SC	TC	IC	FLC	Lead time	Waiting time	Objective functions	Decisions	Model	Constraints
An and Ouyang, (2016)	Single	Single	Three	Yes	No	Yes	No	No	Maximization of profit and minimization of post-harvest losses	Determination of location and grain price	MINLP	Supply, capacity, grain conservation and binary decision variables
Baykasoğlu and Subulan, (2016)	Multi	Multi	Three	Yes	No	No	Yes	No	Minimization of total transport cost, total transit time and total carbon emission	Determination of export and import quantity and corresponding cruises and chartered block trains	MILP	Periodic load allocation for demand satisfaction, specific constraint on marine along with rail transportation and decision variable constraints
Bortolini et al., (2016)	Single	Multi	Two	Yes	No	No	Yes	No	Minimization of operating cost, carbon footprint and delivery time	Determination of shipment quantity	LP	Food quality dependence, market demand and production capacity
Mohammed and Wang, (2017a)	Single	Single	Three	Yes	No	No	Yes	No	Minimization of transportation cost, required transportation vehicles and delivery time	Determination of shipment quantity and corresponding number of expected required vehicles	MILP	Supply, capacity, demand satisfaction, transportation time, number of vehicles determination and decision variable constraints
Mohammed and Wang, (2017b)	Single	Single	Three	Yes	No	No	Yes	No	Minimization of transportation cost, environmental impact, distribution time and maximization of average delivery rate	Determination of opening of farm and abattoir, shipment quantity and corresponding number of expected required labourers	MILP	Supply, capacity, demand satisfaction, number of vehicle determination and decision variable constraints
Harris et al., (2014)	Single	Single	Two	Yes	No	Yes	No	No	Minimization of total cost and CO_2 emission	Determination of number of depots to be opened	LP	Allocation, demand satisfaction and capacity

Table 1 (continued)

Soysal et al., (2014)	Multi	Multi	Four	Yes	Yes	No	No	No	Minimization of total logistics cost and total CO_2 emission	Determination of flow quantities, inventory level, number of fully and less than fully loaded trucks rented	LP	Inventory and product flow balance, demand satisfaction, transport capacity, truck utilization rate and decision variable constraints
Resat and Turkay, (2015)	Multi	Multi	Two	Yes	No	No	Yes	No	Minimization of transportation cost and time	Determination of flow quantity, traffic volume and time duration	MILP	Flow conservation, demand satisfaction, and time dependent traffic congestion constraints
Validi et al., (2014)	Single	Single	Three	Yes	No	No	No	No	Minimization of total cost and CO_2 emission	Determination of the sustainable transportation route	MIP	Demand, route assignment and AHP constraint
Paksoy et al., 2012	Single	Single	Three	Yes	No	No	No	No	Minimization of transportation cost from suppliers to silos and manufactures to warehouses	Determination of various flow quantities	LP	Supply, capacity and demand
Proposed model	Multi	Multi	Four	Yes	Yes	Yes	Yes	Yes	Minimization of total food grain supply chain network cost and total lead time along with Dwell time (DT)	Determination of location, allocation, capacity, inventory and transportation decisions	MINLP	Supply, storage capacity, demand, inventory flow balance, maximum number of silos that can be established, vehicle capacity and availability constraint, decision variable constraints

TC: Transportation cost, IC: Inventory cost, FLC: Facility location cost, MINLP: Mixed integer non-linear programming, MILP: Mixed integer linear programming, MIP: Mixed integer programming, LP: Linear programming

The extensive review of the existing relevant literature indicates that very limited number of studies have been carried out on multi-objective facility location-allocation problems in the food supply chain domain. In order to tackle the grain silo location-allocation problem of the FCI, there is a need for a new mathematical model due to the following reasons. Researchers have mostly focused on the single objective while dealing with the food supply chain problems. The authors who typically worked on multi-objective optimization simultaneously considered the various conflicting objectives like profit and post-harvest losses, cost and carbon emission, and cost and carbon footprint. Few authors have included the time as a one of the objectives along with cost and carbon emission. However, their focus was on load planning and tactical optimization problem. The waiting time of food stock must be taken into account for the quick transfer of food from surplus states to deficit states and reduction of the post-harvest losses. Moreover, a large number of available studies are mainly based on the perishable food supply chain like sugar cane, milk and milk products, and fruits and vegetables. Due to the geographically dispersed surplus and deficit states, food grain is transported through different transportation modes. Hence, multi-modal transportation is an important aspect in the food grain supply chain. The timely availability of heterogeneous capacitated vehicles is another vital feature as it helps in quick transferring of food grain from surplus states to deficit states, reducing the post-harvest losses and minimizing the cost and time. Therefore, various realistic and practical features of the problem such as dwell time, multi-period, multi-echelon, heterogeneous capacitated vehicles and their limited availability at each echelon, multiple sourcing, multi-modal transportation, capacitated base and field silos and vehicle capacity constraints are simultaneously incorporated in our model. In addition, most of the previous papers are related to the food grain supply chain system of a particular country like Iran, Canada, Kenya, United States, Brazil and Turkey, etc. Each country's food grain supply chain system is not similar to any other due to the different procurement seasons, involved entities, geographically dispersed surplus and deficit states, storage as well as transportation systems and other factors. The grain supply chain is a complex dynamic system due to the presence of heterogeneous entities and their complex interactions (Swaminathan et al., 1998). Similarly, Indian food grain supply chain system is distinct and unique compared to other developing countries and it is very complex to manage because of its chaotic nature and the involvement of many entities - farmers, SGAs of surplus and deficit states, FCI, Railways, private contractors and their constraints (Sachan et al., 2005).

3. Problem description

The numerical data given in the introduction section show the huge shortfall of storage capacity with FCI against the central pool stock. In the centralized procurement system, FCI has to take over the wheat stock from SGAs at the end of the procurement season and transfer into their own warehouses. Since FCI doesn't have enough storage capacity to accommodate this stock, they pay the carry-over charges to the various SGAs of procuring states to keep the stock beyond the prescribed time limit. The waiting time of food grains at SGAs warehouses is quite high because of the inadequate storage capacity of FCI. In some cases, the procured stock of food grains of the current year remains unlifted until the end of the following years. Subsequently, several SGAs don't have sufficient covered warehouses for storage beyond the prescribed time limit. Therefore, they use an open storage, i.e., covered and plinth (CAP). Due to the CAP, the quality of the food grain deteriorates and consequential loss of food grain also increases. FCIs owned storage capacity is not even sufficient to accommodate the minimum buffer stock of different states for food security. In order to curtail the waiting time at SGAs warehouses, better preservation and quick transfer from producing states to consuming states of food grains, GOI is creating the modern infrastructure for integrated bulk grain handling, storage and transportation system including the steel silos in various surplus and deficit states.

The considered four-echelon food grain supply chain network as illustrated in Fig. 3, is comprised of procurement centers, base silos, field silos and demand points. The silo location is a strategic decision and needs a lot of investment or fixed cost depending upon its storage capacity for constructing the same. For instance, if the silo of 0.025 MMT capacity is to be constructed, an initial approximate investment of INR 5 million is required. If we try to minimize the lead time comprising of waiting time of stock at SGAs warehouses, FCI needs a large number of silos i.e., huge investments and vice versa. Hence, there is a trade-off between the lead time and supply chain network cost and our objective is to determine the set of compromised solutions to resolve the trade-off among conflicting objectives through multi-objective mathematical modeling. The formulated multi-objective mathematical model with two objective functions and constraints are described in the next section.

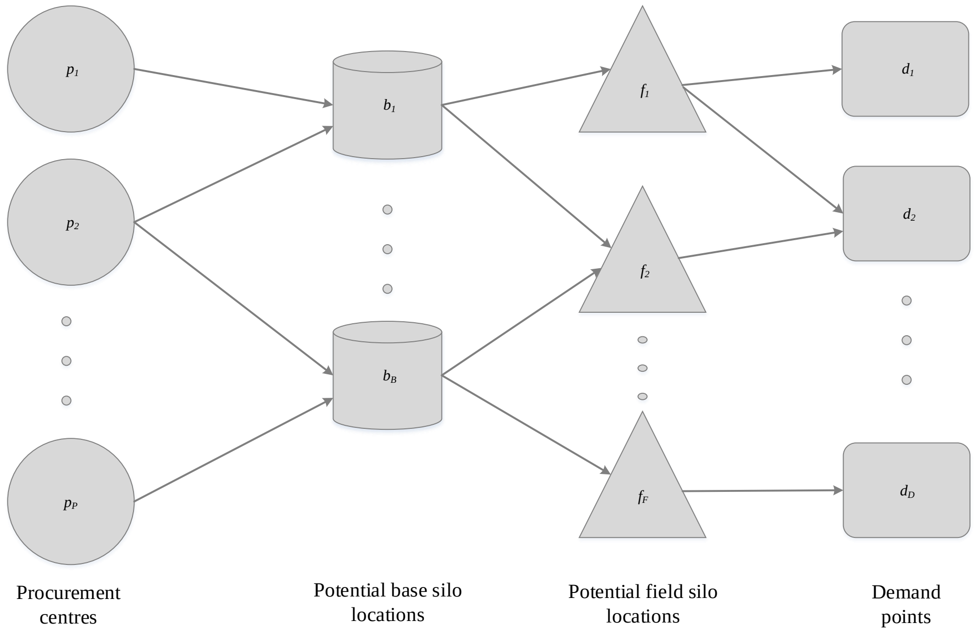


Fig. 3. Four-echelon food grain supply chain network

4. Multi-objective mathematical model

In this section, initially, we discuss the dwell time and its components as well as describe some assumptions considered while developing the model. Then, index sets, model parameters and decision variables are explained. Finally, the two objective functions and constraints used to solve the problem along with explanation are given.

4.1 Dwell time and its components

The lead time of food grain shipment from procurement centres to demand points comprises of the travel time of vehicles and the waiting time (dwell time) of food grain at procurement centres, base silos and field silos. We have not considered the waiting time of food grain at base and field silos because of very less food grain losses. As mentioned previously, due to the inadequate storage capacity of FCI, the waiting time of food grain stock at procurement centre increases, which deteriorate the food grain quality and increase the losses. The dwell time depends on three main factors, i.e., a number of vehicles (trucks) moved from procurement centre to base silo, availability of base silo storage capacity and administrative activities. Firstly, if a sufficient number of vehicles with a full truckload capacity are not moved from procurement centre to base silo in a given time period for food shipment, then food grain stock remains at procurement centre. Secondly, due to the inadequate base silo storage capacity, food grain stock cannot transfer to the base silo. Finally, some administrative activities and other inefficiencies at the procurement centre will increase the waiting time. The sum of time losses due to lack of vehicle movement, unavailability of base silo capacity and administrative activities makes the total waiting time or dwell time (DT) of food grain stock at procurement centre. The dwell time function can be represented as follows:

$$\text{DT} = \mu + \frac{\theta}{\text{Number of vehicles moved from procurement centre to base silo}} + \frac{\xi}{\text{Availability of base silo storage capacity at given location}}$$

The aforementioned formula for calculating the dwell time comprises of three terms. Therein, three constant components including μ, θ and ξ are used to represent various waiting times caused by different motives. The first constant component μ depicts the waiting time at procurement centre due to administrative activities. The time lost due to the insufficient number of vehicles moved from procurement centres to base silos is described by the second constant component θ in the numerator of the second term. Lastly, the constant component ξ is used in the numerator of the third term to indicate the waiting time of food grain stock at procurement centre because of inadequate base silos storage capacity. This DT function is modeled after the critical study of the CAG 2013 report, the High-Level Committee (HLC) 2015 report, other reports of PDS and relevant papers, where all these issues of waiting time are discussed.

4.2 Assumptions:

1. The amount of food grain procured and consumed in each surplus and deficit states, and the capacity of procurement centers are known and deterministic in nature.
2. Potential locations of base and field silo are known and fixed.
3. Three different types of capacitated vehicles (trucks and rakes) are considered for food grain transportation between various echelons.
4. Three types of base and field silos with different but fixed capacities (small, medium and large) are considered.
5. The availability of each capacitated vehicle is finite during a given time period.
6. The amount of food grain procured is adequate to meet the demand.
7. The demand must be fulfilled in a given time period.

4.3 Notations

4.3.1 Index Sets

$\mathbb{P}$	Set of procurement centres $(p = 1, 2, ..., P)$
$\mathbb{B}$	Set of potential base silo locations $(b = 1, 2, ..., B)$
$\mathbb{F}$	Set of potential field silo locations $(f = 1, 2, ..., F)$
$\mathbb{D}$	Set of demand points $(d = 1, 2, ..., D)$
$\mathbb{Q}$	Set of base silo types ($q = s$ (small size), m (medium size), l (large size))
$\mathbb{R}$	Set of field silo types ($r = \hat{s}$ (small size), $\hat{m}$ (medium size), $\hat{l}$ (large size))
$\mathbb{I}$	Set of truck types available at procurement centre $(i = 1, 2, ..., I)$
$\mathbb{J}$	Set of rake types available at base silo $(j = 1, 2, ..., J)$
$\mathbb{K}$	Set of truck types available at field silo $(k = 1, 2, ..., K)$
$\mathbb{T}$	Set of time periods $(t = 1, 2, ..., T)$

4.3.2 Model parameters

α_{pb}	Transportation cost by trucks from procurement centre to base silo (Unit cost/Km)
α_{bf}	Transportation cost by rails from base silo to field silo (Unit cost/Km)
α_{fd}	Transportation cost by trucks from field silo to demand point (Unit cost/Km)
ω_{pb}	Distance from procurement centre p to base silo b (Km)
ω_{bf}	Distance from base silo b to field silo f (Km)
ω_{fd}	Distance from field silo f to demand point d (Km)
φ_b^q	Fixed cost of construction of base silo of type q at location b $(q = s,\ m,\ l)$

φ_f^r	Fixed cost of construction of field silo of type *r* at location *f* $\left(r = \hat{s},\ \hat{m},\ \hat{l}\right)$
ϕ_b	Inventory holding cost per unit time period in base silo *b* (MT/period)
ϕ_f	Inventory holding cost per unit time period in field silo *f* (MT/period)
M_d^t	Demand of demand points (distrcit level warehouses) *d* in time period *t*
G_p^t	Food grain quantity available at procurement centre *p* in time period *t*
ε_b^q	The capacity of the base silo of type *q* at location *b* $\left(q = s,\ m,\ l\right)$
ε_f^r	The capacity of the field silo of type *r* at location *f* $\left(r = \hat{s},\ \hat{m},\ \hat{l}\right)$
τ_{pb}	Transit time from procurement centre *p* to base silo *b*
τ_{bf}	Transit time from base silo *b* to field silo *f*
τ_{fd}	Transit time from field silo *f* to demand point *d*
π_{ip}^t	Number of trucks of type *i* available at procurement centre *p* in time period *t*
cap_i	Capacity of a truck of type *i*
π_{jb}^t	Number of rakes of type *j* available at base silo *b* in time period *t*
cap_j	Capacity of a rake of type *j*
π_{kf}^t	Number of trucks of type *k* available at field silo *f* in time period *t*
cap_k	Capacity of a truck of type *k*
M	A sufficiently large number
U_b^q	Maximum number of base silos of type *q* that can be constructed in all potential base silo locations
N_f^r	Maximum number of field silos of type *r* that can be established in all potential field silo locations

4.3.3 Decision variables

Binary Variables

$$E_b^q = \begin{cases} 1 & \text{If a base silo of type } q \text{ is to be constructed at location } b, \\ 0 & \text{otherwise,} \end{cases}$$

$$H_f^r = \begin{cases} 1 & \text{If a field silo of type } r \text{ is to be constructed at location } f, \\ 0 & \text{otherwise,} \end{cases}$$

$$X_{pb}^t = \begin{cases} 1 & \text{If procurement centre } p \text{ transports the food grain to base silo } b \text{ in time period } t, \\ 0 & \text{otherwise,} \end{cases}$$

$$Y_{bf}^t = \begin{cases} 1 & \text{If base silo } b \text{ transports the food grain to field silo } f \text{ in time period } t, \\ 0 & \text{otherwise,} \end{cases}$$

$$Z_{fd}^t = \begin{cases} 1 & \text{If field silo } f \text{ transports the food grain to demand point } d \text{ in time period } t, \\ 0 & \text{otherwise,} \end{cases}$$

Continuous Variables

a_{pb}^t The amount of food grain quantity transported from procurement centre p to base silo b in time period t

g_{bf}^t The amount of food grain quantity transported from base silo b to field silo f in time period t

ρ_{fd}^t The amount of food grain quantity transported from field silo f to demand point d in time period t

W_b^t Inventory available in the base silo b at the end of period t

V_f^t Inventory available in the field silo f at the end of period t

Dwell time function

$DTPB_{pb}^t$ = Average Dwell time between procurement centre p to base silo b in time period t

$$DTPB_{pb}^{t} = \begin{cases} \mu_{pb} + \dfrac{\theta_{pb}}{\left(\sum_{i=1}^{I} m_{pb}^{it} cap_i\right)} + \dfrac{\xi_{pb}}{\left(\sum_{q=1}^{Q} \varepsilon_b^q E_b^q - W_b^t\right)} & \text{If } X_{pb}^{t} = 1, \\ 0 & \text{otherwise,} \end{cases}$$

Here, μ_{pb}, θ_{pb} and ξ_{pb} are constants.

Integer Variables

m_{pb}^{it} Number of trucks of type *i* used for food grain transportation between procurement centre *p* to base silo *b* during time period *t* (number of trucks/time period).

n_{bf}^{jt} Number of rakes of type *j* used for food grain transportation between base silo *b* to field silo *f* during time period *t* (number of rakes/time period).

s_{fd}^{kt} Number of trucks of type *k* used for food grain transportation between field silo *f* to demand point *d* during time period *t* (number of trucks/time period).

4.4 Objective function

The objective of the model is to determine the optimum base and field silo locations along with their capacities, the flow of food grain between various echelons and inventory at base and field silos such that the total supply chain network cost and lead time are minimized. Two conflicting objective functions are developed in the model. The minimization of the total supply chain network cost is the first objective which consists of transportation cost, silo construction cost and inventory cost. The transportation cost includes the cost from procurement centre to the base silo, base silo to field silo and field silo to demand point which is represented by Eq. (1). The Eq. (2) gives the silo construction cost which consists of fixed construction cost of base and field silos. The sum of inventory holding cost at base and field silos represents the total inventory cost in the first objective which is shown by Eq. (3). The second objective is the minimization of lead time of food grain supply chain network and consists of three main components. The lead time from procurement centres to base silos along with dwell time at procurement centre is the first component which is indicated in Eq. (4). Second and third components which are illustrated by Eqs. (5) and (6) are the lead time from base silos to field silos and field silos to demand points, respectively. These two conflicting objectives are described as follows:

First objective

Minimize total network cost =Transportation cost + Silo construction cost + Inventory cost

Components of first objective

Transportation cost = Transportation cost from procurement centre to base silo +
Transportation cost from base silo to field silo +
Transportation cost from field silo to demand point.

Transportation cost =

$$\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{t=1}^{T}\alpha_{pb}\omega_{pb}a_{pb}^{t} + \sum_{b=1}^{B}\sum_{f=1}^{F}\sum_{t=1}^{T}\alpha_{bf}\omega_{bf}g_{bf}^{t} + \sum_{f=1}^{F}\sum_{d=1}^{D}\sum_{t=1}^{T}\alpha_{fd}\omega_{fd}\rho_{fd}^{t} \qquad (1)$$

Silo construction cost = Fixed cost of base silo construction +
Fixed cost of field silo construction

Silo construction cost = $\sum_{b=1}^{B}\sum_{q=1}^{Q}\varphi_{b}^{q}E_{b}^{q} + \sum_{f=1}^{F}\sum_{r=1}^{R}\varphi_{f}^{r}H_{f}^{r}$ (2)

Inventory cost = Inventory cost at base silo + Inventory cost at field silo

Inventory cost = $\sum_{b=1}^{B}\sum_{t=1}^{T}\phi_{b}W_{b}^{t} + \sum_{f=1}^{F}\sum_{t=1}^{T}\phi_{f}V_{f}^{t}$ (3)

Second objective

Minimize total lead time =

Dwell time and lead time from procurement centre to base silo +
Lead time from base silo to field silo +
Lead time from field silo to demand point

Components of second objective

Dwell time and lead time from procurement centre to base silo =

$$\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{i=1}^{I}\sum_{t=1}^{T}\left(DTPB_{pb}^{t}+\tau_{pb}m_{pb}^{it}\right) \tag{4}$$

Lead time from base silo to field silo = $\sum_{b=1}^{B}\sum_{f=1}^{F}\sum_{j=1}^{J}\sum_{t=1}^{T}\left(\tau_{bf}n_{bf}^{jt}\right)$ (5)

Lead time from field silo to demand point = $\sum_{f=1}^{F}\sum_{d=1}^{D}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(\tau_{fd}s_{fd}^{kt}\right)$ (6)

Subject to Constraints

$$\sum_{b=1}^{B}a_{pb}^{t}\le G_{p}^{t} \qquad \forall p,\forall t \tag{7}$$

$$a_{pb}^{t}\le MX_{pb}^{t} \qquad \forall p,\forall b,\forall t \tag{8}$$

$$X_{pb}^{t}\le\sum_{q=1}^{Q}E_{b}^{q} \qquad \forall p,\forall b,\forall t \tag{9}$$

Constraint (7) limits the food grain quantity transported from procurement centre to all constructed base silos to maximum food grain quantity available at the given procurement centre during each time period. Constraint (8) ensures that the food grain quantity can be transferred from procurement centre to base silo only if procurement centre is allocated to the base silo. Similarly, Constraint (9) make sure that the procurement centre can be allocated to base silo if base silo is constructed.

$$\sum_{f=1}^{F}g_{bf}^{t}\le W_{b}^{t} \qquad \forall b,\forall t \tag{10}$$

$$g_{bf}^{t}\le MY_{bf}^{t} \qquad \forall b,\forall f,\forall t \tag{11}$$

$$Y_{bf}^{t}\le\sum_{q=1}^{Q}\sum_{r=1}^{R}E_{b}^{q}H_{f}^{r} \qquad \forall b,\forall f,\forall t \tag{12}$$

$$Y_{bf}^{t}\le\sum_{q=1}^{Q}\sum_{r=1}^{R}L_{bf}^{qr} \qquad \forall b,\forall f,\forall t \tag{12a}$$

$$\sum_{q=1}^{Q} E_b^q + \sum_{r=1}^{R} H_f^r \geq 2\sum_{q=1}^{Q}\sum_{r=1}^{R} L_{bf}^{qr} \qquad \forall b, \forall f \tag{12b}$$

$$\sum_{q=1}^{Q} E_b^q + \sum_{r=1}^{R} H_f^r - \sum_{q=1}^{Q}\sum_{r=1}^{R} L_{bf}^{qr} \leq 1 \qquad \forall b, \forall f \tag{12c}$$

Constraint (10) shows that food grain quantity transferred from established base silos is less than or equal to the maximum inventory available at given base silo during that period. Constraint (11) implies that food grain can be shipped from base to field silo only if the base silo is allocated to the field silo. The base silo can be assigned to the field silo only if both base and field silo are established and it is depicted by Constraint (12). This constraint is nonlinear because of the multiplication of two binary variables, i.e., E_b^q and H_f^r. In order to linearize this constraint, a new binary variable L_{bf}^{qr} is introduced which takes the value 1 if both E_b^q and H_f^r take the value 1 else remains 0. Therefore, Constraints (12a) to (12c) are used to ensure the linearization of Constraint (12). It means that either Constraint (12) or Constraints set (12a) to (12c) should appear in the model.

$$\sum_{d=1}^{D} \rho_{fd}^t \leq V_f^t \qquad \forall f, \forall t \tag{13}$$

$$\rho_{fd}^t \leq M Z_{fd}^t \qquad \forall f, \forall d, \forall t \tag{14}$$

$$Z_{fd}^t \leq \sum_{r=1}^{R} H_f^r \qquad \forall f, \forall d, \forall t \tag{15}$$

Furthermore, Constraints set (13) and (14) portrays the supply constraint of field silo and big *M* constraint respectively. Constraint (15) states that the field silo can be assigned to demand point only if field silo is constructed.

$$W_b^{t-1} + \sum_{p=1}^{P} a_{pb}^t \leq \sum_{q=1}^{Q} \varepsilon_b^q E_b^q \qquad \forall b, \forall t \tag{16}$$

$$V_f^{t-1} + \sum_{b=1}^{B} g_{bf}^t \leq \sum_{r=1}^{R} \varepsilon_f^r H_f^r \qquad \forall f, \forall t \tag{17}$$

Constraints (16) and (17) make sure that inventory at base and field silo does not exceed their inventory holding capacity.

$$\sum_{f=1}^{F} \rho_{fd}^{t} = M_{d}^{t} \qquad \forall d, \forall t \tag{18}$$

Constraint (18) illustrates that food grain quantity shipped from all field silos is equal to the demand of demand point (district level warehouse).

$$\sum_{b=1}^{B} E_{b}^{q} \leq U_{b}^{q} \qquad \forall q \tag{19}$$

$$\sum_{f=1}^{F} H_{f}^{r} \leq N_{f}^{r} \qquad \forall r \tag{20}$$

Constraint (19) restricts the maximum number of base silos of type *q* that can be established in a particular surplus state. Similarly, Constraint (20) shows the maximum limit of the number of field silos of type *r* to be constructed in a given deficit state.

$$\sum_{q=1}^{Q} E_{b}^{q} \leq 1 \qquad \forall b \tag{21}$$

$$\sum_{r=1}^{R} H_{f}^{r} \leq 1 \qquad \forall f \tag{22}$$

Constraints (21) and (22) guarantee that at most one type of base silo ($q = s,\ m,\ l$) and field silo ($r = \hat{s},\ \hat{m},\ \hat{l}$) can be constructed at each potential base and field silo locations, respectively.

$$W_{b}^{t-1} + \sum_{p=1}^{P} a_{pb}^{t} - \sum_{f=1}^{F} g_{bf}^{t} = W_{b}^{t} \qquad \forall b, \forall t \tag{23}$$

$$V_{f}^{t-1} + \sum_{b=1}^{B} g_{bf}^{t} - \sum_{d=1}^{D} \rho_{fd}^{t} = V_{f}^{t} \qquad \forall f, \forall t \tag{24}$$

Flow conservation at every base and field silo is represented by Constraints (23) and (24), respectively.

$$a_{pb}^{t} \leq \sum_{i=1}^{I} m_{pb}^{it} cap_{i} \qquad \forall p, \forall b, \forall t \tag{25}$$

$$g_{bf}^{t} \le \sum_{j=1}^{J} n_{bf}^{jt} cap_{j} \qquad \forall b, \forall f, \forall t \tag{26}$$

$$\rho_{fd}^{t} \le \sum_{k=1}^{K} s_{fd}^{kt} cap_{k} \qquad \forall f, \forall d, \forall t \tag{27}$$

Constraint (25) represents the truck capacity constraint between procurement centre and base silo. In the similar way, rake capacity constraint between the base silo and the field silo is depicted by constraint (26). Constraint (27) describes the truck capacity constraint from field silo to demand point.

$$DTPB_{pb}^{t} \le MX_{pb}^{t} \qquad \forall p, \forall b, \forall t \tag{28}$$

$$m_{pb}^{it} \le MX_{pb}^{t} \qquad \forall p, \forall b, \forall i, \forall t \tag{29}$$

$$n_{bf}^{jt} \le MY_{bf}^{t} \qquad \forall b, \forall f, \forall j, \forall t \tag{30}$$

$$s_{fd}^{kt} \le MZ_{fd}^{t} \qquad \forall f, \forall d, \forall k, \forall t \tag{31}$$

Constraint (28) guarantees that DT between procurement centre to base silo exists if procurement centre is allocated to the base silo. In addition, heterogeneous capacitated vehicles can be moved from procurement centre to the base silo if procurement centre is assigned to the base silo and it is defined by Constraint (29). In the same way, Constraints set (30) indicates the restriction on a number of heterogeneous capacitated vehicles moved from the base silo to the field silo unless the base silo is allocated to the field silo. Constraint (31) represents the relationship between the s_{fd}^{kt} and Z_{fd}^{t} using the big M constraint.

$$\sum_{b=1}^{B} m_{pb}^{it} \le \pi_{ip}^{t} \qquad \forall p, \forall i, \forall t \tag{32}$$

$$\sum_{f=1}^{F} n_{bf}^{jt} \le \pi_{jb}^{t} \qquad \forall b, \forall j, \forall t \tag{33}$$

$$\sum_{d=1}^{D} s_{fd}^{kt} \le \pi_{kf}^{t} \qquad \forall f, \forall k, \forall t \tag{34}$$

Constraint (32) limits the number of trucks used from the procurement centre to base silos to maximum trucks available at the procurement centre during each time period. Correspondingly, Constraints (33) and (34) depict the restriction on a number of vehicles (rakes and trucks) utilized between base silo to field silos and field silo to demand points, respectively.

$$E_b^q \in \{0,1\} \qquad \forall b, \forall q \tag{35}$$

$$H_f^r \in \{0,1\} \qquad \forall f, \forall r \tag{36}$$

$$X_{pb}^t \in \{0,1\} \qquad \forall p, \forall b, \forall t \tag{37}$$

$$Y_{bf}^t \in \{0,1\} \qquad \forall b, \forall f, \forall t \tag{38}$$

$$Z_{fd}^t \in \{0,1\} \qquad \forall f, \forall d, \forall t \tag{39}$$

Constraints (35) - (39) denote the binary variables.

$$m_{pb}^{it} \in \mathbb{Z}^+ \qquad \forall p, \forall b, \forall i, \forall t \tag{40}$$

$$n_{bf}^{jt} \in \mathbb{Z}^+ \qquad \forall b, \forall f, \forall j, \forall t \tag{41}$$

$$s_{fd}^{kt} \in \mathbb{Z}^+ \qquad \forall f, \forall d, \forall k, \forall t \tag{42}$$

The integer variables are represented by constraints (40) – (42).

$$a_{pb}^t \geq 0 \qquad \forall p, \forall b, \forall t \tag{43}$$

$$g_{bf}^t \geq 0 \qquad \forall b, \forall f, \forall t \tag{44}$$

$$\rho_{fd}^t \geq 0 \qquad \forall f, \forall d, \forall t \tag{45}$$

$$W_b^t \geq 0 \qquad \forall b, \forall t \tag{46}$$

$$V_f^t \geq 0 \qquad \forall f, \forall t \tag{47}$$

Finally, non-negativity constraints are indicated by constraints (43) - (47).

The above-described mathematical model comprises of non-linear dwell time function and several decision variables including binary, integer and continuous along with real-life constraints like supply, capacity, demand, inventory flow balance and vehicle capacity, etc. The second objective function and constraint (28) become the non-linear due to the non-linearity of dwell time function. Many well-known conventional methods like ε constraint method (ECM), goal programming and weighted sum method (WSM) exist to solve the multi-objective model. However, these approaches transform the multi-objective model into single objective and then optimize the transformed single objective model (Jones et al., 2002). In addition, most of these techniques provide only one optimal point on the efficient Pareto Frontier in a single iteration, whereas "Multi-objective Evolutionary algorithms (MOEAs)" simultaneously develop a set of solutions at various points along the trade-off surface using the Pareto optimality and modified selection schemes (Deb, 2001). Unlike classical methods, MOEAs determine a set of Pareto-optimal solutions in a single iteration. The MOEAs are becoming popular among the researchers to solve the multi-objective models because of following features. 1) The population based approach, 2) Determination of multiple Pareto optimal solutions in a single simulation run, 3) Simple in implementation and 4) Feasibility of utilization on large parameter search spaces (Goh and Tan, 2009).

Furthermore, the conventional technique based commercial software are incapable of solving the multi-objective model with non-linear and discrete decision variables (Yu et al., 2017). Hence, several MOEAs like NSGA-II (Cheshmehgaz et al., 2013), multi-objective vibration damping optimization (Hajipour et al., 2016), multi-objective biogeography based optimization (Sarrafha et al., 2015) and multi-objective hybrid particle swarm optimization (Shankar et al., 2013) algorithms have been utilized to address the complex multi-objective models. Therefore, recently developed NCRO algorithm (Bechikh et al., 2015) is employed to solve the mathematical model and obtained results are validated through NSGA-II algorithm (Deb et al., 2002).

5. Solution approach

The NCRO algorithm is inspired by the CRO algorithm and consist of few similar types of operators like two uni-molecular reactions and two intermolecular reactions. Thus, initially, we briefly describe the CRO algorithm as well as its features and then NCRO algorithm along with its flowchart and pseudocode in detail.

5.1 CRO: Basic algorithm and features

CRO algorithm developed by Lam and Li, (2010) which is inspired from the chemical reaction phenomenon of molecules. The molecule is the main operating agent in CRO similar to the chromosome in GA and the solution of a particular problem is stored in it. Some basic attributes of molecule are as follows. The molecular structure represents the encoding scheme of a particular problem. The potential energy (PE) shows the objective function value of the considered molecule. The kinetic energy (KE) is used as a measure of tolerance to accept the worst solution than existing one for jumping out from the local minima. The population of molecules is generated using the four chemical reactions in which two reactions are uni-molecular and remaining two are multi-molecular. On-wall ineffective collision and decomposition reactions are unimolecular whereas intermolecular ineffective and synthesis fall under the category of intermolecular reactions. These chemical reactions work as variation operators in CRO for environmental selection. The interested readers can refer to Lam et al., (2012) for comprehensive information about the CRO algorithm. The four variation operators (elementary chemical reaction) are described as follows.

1) *On-wall ineffective collision:* In this reaction, a single molecule hits the wall of the container and then bounces back as a single unit. The new molecule is generated by perturbing the original molecule using the neighbourhood operator. Thus, its structure is not too much different from the original molecule.
2) *Decomposition:* This reaction takes place when a molecule collides with the wall of the container and splits into many parts (considered two parts in this paper). CRO algorithm uses this operator for exploration of new search space after the local search carried out by ineffective collisions.
3) *Intermolecular ineffective collision:* It corresponds to the situation when two randomly generated molecules collide with each other and create two new molecules. This reaction is very similar to the on-wall ineffective collision and searches many neighbourhoods simultaneously.
4) *Synthesis:* This operator performs the opposite action of the decomposition reaction. It occurs when many molecules (assumed two in this paper) hit against each other and form a new molecule.

5.2 NCRO basic scheme

NCRO follows the same flow as of NSGA-II in a different manner. Initially, the problem specific information including values of model parameters, number of decision variables and number of objectives are provided in the form of input. Also, calibrated values obtained through Taguchi method are assigned to the algorithmic control parameters involving *PopSize, KELossRate, MoleColl, InitialKE,* and α, β etc. Next, the main algorithm will begin by randomly generating the initial population. The algorithm sequentially executes the following steps: offspring generation, revise generated offspring, combining parent and offspring, Quick Non-Dominated Sorting Algorithm (Q-NDSA), crowding distance assignment, PE assignment and determination of best non-dominated solutions, etc. CRO variation operators such as decomposition, synthesis, on-wall ineffective and inter-molecular ineffective are employed for obtaining the offspring (Q_t) from the parent population (P_t). Due to the energy management laws of CRO which control the number of moves, Q_t population must be revised. The modifications are done so as to make CRO compatible with NSGA-II scheme. These include assignment of PE (presented in subsection 5.2.1) to the population and generation of offspring (presented in subsection 5.2.2). As soon as the offspring population is formed and revised, we combine both the parent and the offspring population, thereby ensuring elitism, i.e., $R_t = P_t + Q_t$. As a result of combining the parent and offspring, the size of the population will be greater than N and less than or equal to 2N. The combined population is sorted using Quick Non-Dominated Sorting Algorithm presented in subsection 5.2.3. Then, PE values are assigned to the combined population using the PE assignment formula which uses Pareto rank and crowding distance measure as parameters. Solutions with low value of PE are the best ones in the combined population. The *N*-best solutions among the population are selected based on PE values and are used as a parent population for the next iteration where another set of offspring is generated. Thus, repeating this procedure until a stopping criteria is reached. The delineation of NCRO algorithm with various operators and their satisfaction criteria is illustrated in Fig. 4 in the form of a flowchart. Additionally, the pseudocode of NCRO is shown in Fig. 5.

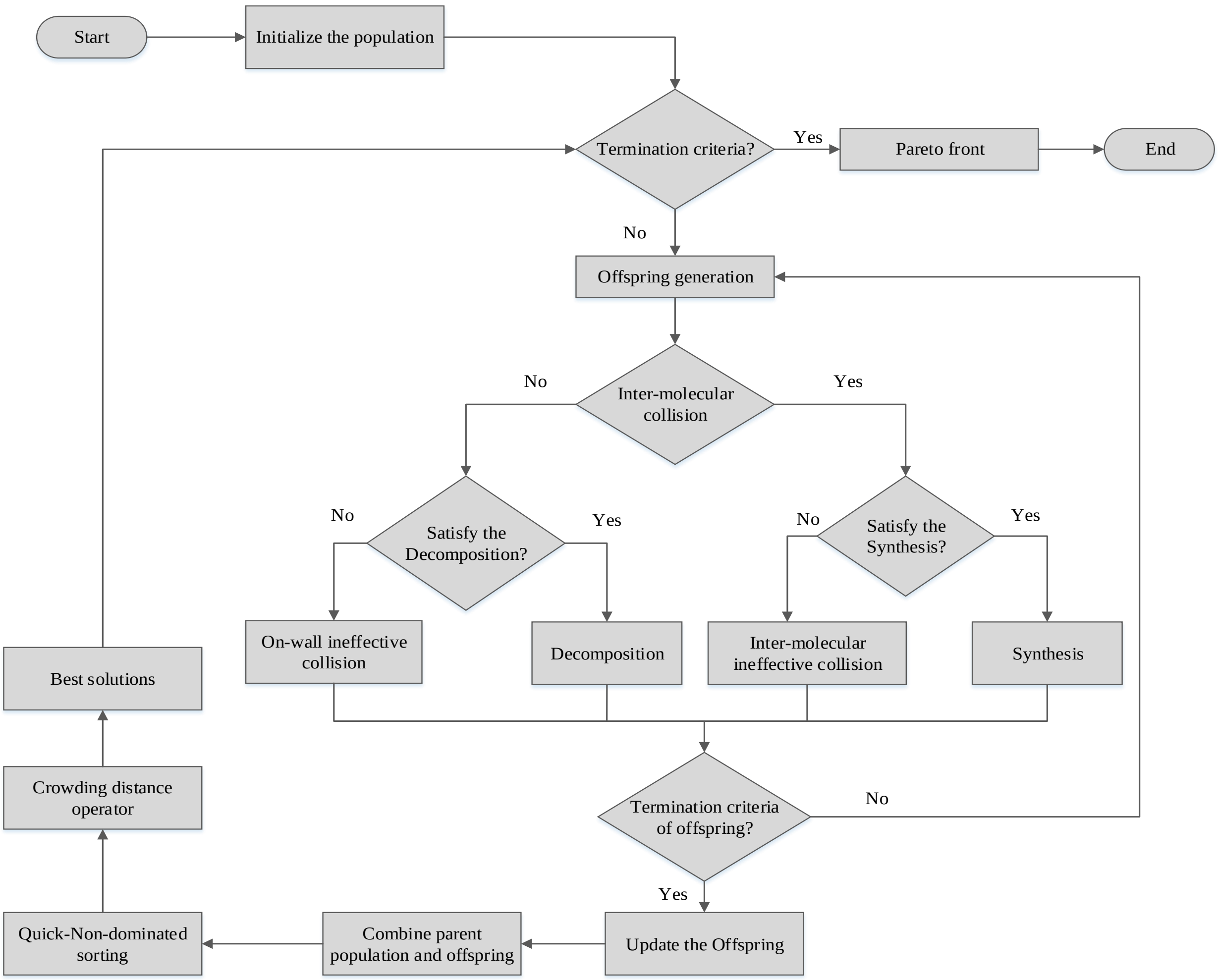


Fig. 4. Flowchart of NCRO

Pseudocode (NCRO)
Input : Problem specific information including number of objectives,
number of decision variables etc. and algortihmic parametrs like
PopSize, *KELossRate*, *MoleColl*, *InitialKE*, α, β *etc.*
Start
Iter(t) = 0 //Iteration count
Pop (P_t) = Initial population
While the termination criteria not satisfy **do**
Q_t = CROVariation (P_t)
Q_t = Update the potential energy of the population (Q_t)
Pop (P_{t+1}) = $P_t \cup Q_t$ //combine the parent and child populations
Pop (P_{t+1}) = **Q - NDSA** (P_{t+1})
Pop (P_{t+1}) = **Crow_Distance Assignement** (P_{t+1})
Pop (P_{t+1}) = Apply the Potential Energy Formula (P_{t+1})
Pop (P_{t+1}) = Take the best solutions among the combined population (P_{t+1})
Iter(t) = Iter(t)+1
End while
End
Output : Pareto front approximation

Fig. 5. Pseudocode of NCRO

5.2.1 PE Assignment operator

In the single objective case, we directly use the objective function as the potential energy or the fitness function. However, in case of bi-objective scenario, the same scheme cannot be applied for evaluating the quality of the molecule. Hence, the following new formula using the Pareto rank and crowding distance of a molecule is proposed.

$$PE(x) = rank(x) + e^{(-crowd(x))} \tag{48}$$

Where *x* is the decision vector, rank *(x)* represents the Pareto rank of that particular solution and crowd *(x)* denotes the crowding distance of that solution which is calculated in the same way as in NSGA-II. This formula helps in evaluating the solutions in the same way as in NSGA-II. If two or more solutions of the same rank are present, then the one with the highest crowding distance is preferred compared to the solution having the least crowding distance. This fitness formula retains the Pareto dominance relation.

5.2.2 Generation of Offspring

The CRO is unique compared to other evolutionary algorithms as its offspring is generated from various operations. When an offspring is produced, we update their potential energy and combine them with the parent population. In order to appropriately apply the CRO energy management laws for updating the offspring population, the number of offspring produced, its child and collision type performed on each molecule is marked. If the parent and offspring do not obey the energy management laws, their children will be removed from offspring population. As a result, the total energy in the system remains constant.

5.2.3 Quick Non-Dominated Sorting (Q-NDSA)

The fundamental concept of Q-NDSA for the bi-objective problem is explained as follows. Initially, sorting of all the population members is carried out based on the first objective. The preceding solutions of a particular solution may dominate it, but the following solutions cannot dominate the same. A Pareto rank 1 is given to the first solution (a solution having the least first objective value). Now, to find the rest non-dominated solutions, we take values of the second objective of the next solution into account based on the sorting done by the first objective. The second objective value of the first solution is stored in a witness variable. If the second objective value of the current solution is less than that of the witness variable, then the solution is non-dominated. Once the first set of non-dominated solutions is identified, we remove them from the solution set and repeat the same process so as to find the next set of non-dominated solutions. Iterations go on until all the solutions are assigned a Pareto rank. The whole procedure of Q-NDSA is represented in Fig. 6 in the form of pseudocode.

```
Pseudocode : Q - NDSA
Input :  Population M
Start
  M = QuickSort (M, 1) //Sort M according to the first objective
  Assign rank 1
  Initialise Pareto Front F
While (M ≠ ϕ) do //termination criterion
    // Find the actual best front from M
   // Find the first non-dominated solutions
     W = s_1.ObjValue(2) // S is the second objective of
     current solution set having minimum first objective value
  For each s_i ∈ M do
     If (s_i.ObjValue(2) ) < W Then // S_i is not dominated by S_1
        W = s_i.ObjValue(2)
        s_i.Rank = Rank
        F = Union (F, s_i) // Keep the same front solutions
            in a temporary variable F */
        M = Remove (s_i, M) // Remove the current solution
          from current solution set
     End If
  End for
     Rank Increment
End while
End
Output :  Ranked Population M
```

Fig. 6. Pseudocode of Q-NDSA

5.3 Non-Dominated Sorting Genetic algorithm II (NSGA-II)

The various steps of NSGA-II algorithm are described in this subsection as follows.

5.3.1 Chromosome structure and initialization

The decision variables are represented in the form of a multi-dimensional arrays, where all the decision variables become a part of a chromosome structure which represents a solution. The decision variables value are either given as an input or are selected randomly from a range of values.

5.3.2 Non-Dominated Sorting

Non-dominated set contains a population of solutions where no solution dominates the other solution in that set. These various sets are called fronts in multi-objective case. We combine the parent and the offspring population and then we do the sorting. For each individual in the combined set, we calculate the number of solutions that dominate the solution p as n_p and the set of solutions which is dominated by p as S_p. All the solutions having n_p value zero are added to the first set of non-dominated solutions. For all the population with n_p=0, we traverse through the solutions in S_p and go on diminishing the domination value until it reaches zero. Then all these solutions are isolated in another list, which forms the second set of non-dominated solutions or the second front. Now the same is followed by the new list of the population and successive fronts are found out.

5.3.3 Crowding Distance

This parameter tells us how much a particular solution is surrounded by other solutions in the population. In order to find the crowding distance of a particular solution, we determine the average distance of two neighbouring solutions on either side of the solution along each objective function. Its calculation requires the normalization of each objective function and sorting of the population in ascending order according to an objective function value. At first, a crowding distance of infinity is assigned for boundary solutions. Then the crowding distance is calculated for the other solutions as the absolute difference of the function values of the neighbouring solutions. In the same way, again the distances are found out after sorting according to other objective functions and the final crowding distance is calculated as the sum of all the distances corresponding to each objective function.

5.3.4 Genetic Operators

Genetic operators are used to perform operations on current population so as to produce the offspring. The two major operators, i.e., mutation and crossover are employed to get diversity in solutions and to combine previous solutions into others. Simulated binary crossover and polynomial mutation operators are used to solve the formulated model.

5.3.5 Selection

Selection is carried out for determining the individuals of the next generation after the offspring population combines with present population. Once the solutions are sorted and crowding distances are assigned, crowd comparison operator is applied to select the best set of solutions. The solution with the least rank is preferred more, but if two solutions possess the same rank, then the solution with the highest crowding distance is preferred. The overall procedure of the NSGA-II algorithm is illustrated using flowchart and pseudocode in Fig. 7 and Fig. 8, respectively.

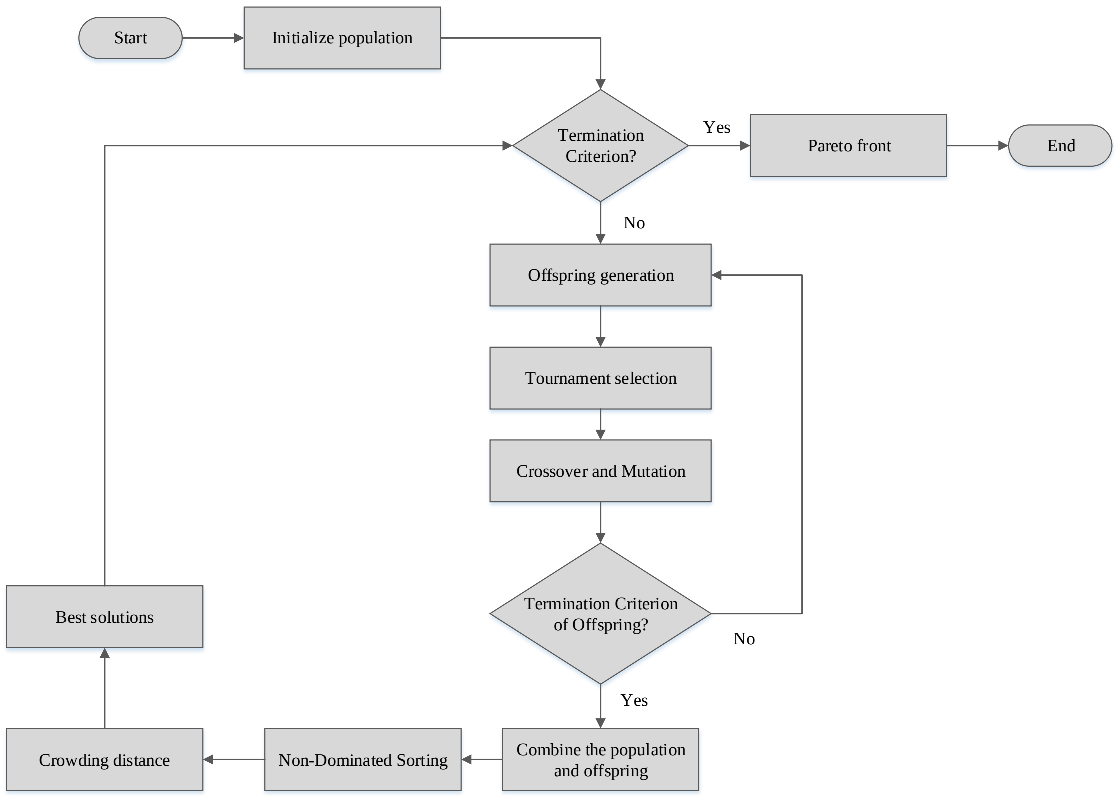


Fig. 7. Flowchart of NSGA-II

```
Start
Population (n)        // Initialise the Population set with length 'n'
 While( Termination condition is not satisfy)
        Parent = Tournament selection of Population
        Offspring = genetic (Parent)
  //Crossover or Mutation is based on probability to generate offspring
  Population = Offspring U Population
  Non Dominated Sorting : Population
  Crowding Distance Assignment: Population
  Selection (Population)
  //selecting the best population based on crowding distance and pareto rank
 End while
End
```

Fig. 8. Pseudocode of NSGA-II

6. Computational results and discussion

In this section, we describe the various generated problem instances, parameter tuning of algorithms and the computational results. Further, the sensitivity analysis of the model and managerial insights are also discussed.

6.1 Problem instances

In order to verify and validate the formulated model and effectiveness of solution approach, 15 problem instances are generated randomly based on the simulated data obtained from many reliable sources such as CAG report 2013, HLC report 2015, FCI portal (http://fci.gov.in) and PDS Portal of India (http://pdsportal.nic.in/main.aspx), etc. In these problem instances, the geographically dispersed major surplus states such as Punjab, Haryana, Madhya Pradesh, Uttar Pradesh, Rajasthan and deficit states like Maharashtra, Tamilnadu, Karnataka, West Bengal, etc. are covered. These instances depend on the supply chain network configuration which comprises of the number of procurement centres (P), number of potential base silo locations (B), number of potential field silo locations (F) and number of demand points (D). Moreover, all the problem instances are classified into small, medium and large scale category considering the number of supply chain facilities in the model. The characteristics of these problem instances are given in Table 2. The summary of the important input parameter values of the model is mentioned in Table 3. In addition, Table 4 provides the comprehensive description of each type of total decision variables and a total number of constraints exist in all problem instances. These total number of decision variables and constraints of all problem instances depicts the complexity of the model.

Table 2 The characteristics of the problem instances

Problem size	Procurement centres (P)	Potential base silo locations (B)	Potential field silo locations (F)	Demand points (D)	Time period (T)
Small	3-15	2-8	4-13	6-20	2
Medium	16-30	9-15	14-25	21-35	3
Large	31-60	16-25	26-35	36-60	4

Table 3 The values of input parameters of the model

Parameters	Range of values	Parameters	Range of values
α_{pb}	20	$\pi^t_{i_3p}$	700-1200
α_{bf}	15	$\pi^t_{j_1b}$	6-15
α_{fd}	20	$\pi^t_{j_2b}$	8-18
ω_{pb}	15-50	$\pi^t_{j_3b}$	9-20
ω_{bf}	400-800	$\pi^t_{k_1f}$	600-1000
ω_{fd}	20-80	$\pi^t_{k_2f}$	700-1100
φ^q_b	3.0×10^7, 4.0×10^7, 5.0×10^7	$\pi^t_{k_3f}$	800-1200
φ^r_f	5.0×10^6, 1.0×10^7, 1.5×10^7	cap_i (i = 1, 2, 3)	20, 18, 15
ϕ_b	100	cap_j (j = 1, 2, 3)	3000, 1800, 1500
ϕ_f	80	cap_k (k = 1, 2, 3)	30, 25, 20
M^t_d	12000-25000	τ_{pb}	2-6
G^t_p	20000-40000	τ_{bf}	80-150
ε^q_b	150000, 200000, 250000	τ_{fd}	4-10
ε^r_f	25000, 50000, 75000	U^q_b	2-23
$\pi^t_{i_1p}$	500-1000	N^r_f	3-35
$\pi^t_{i_2p}$	600-1100		

Table 4 Depicting the problem sizes, different variables and constraints

Problem Size	Problem number	Procurement centres (P)	Potential base silo locations (B)	Potential field silo locations (F)	Demand points (D)	Time period (T)	Total number of constraints	Binary variables	Continuous variables	Integer variables
Small size	1	5	3	4	7	2	1332	142	104	276
	2	8	4	6	10	2	3298	344	252	696
	3	10	5	8	13	2	5408	551	414	1164
	4	12	6	10	15	2	7816	786	596	1692
	5	15	8	13	20	2	13262	1310	1010	2904
Medium size	6	18	10	15	22	3	25858	2685	2055	5940
	7	20	11	17	25	3	32419	3342	2580	7488
	8	23	13	18	28	3	40378	4209	3204	9333
	9	26	14	22	32	3	53250	5460	4236	12384
	10	30	15	25	35	3	65551	6720	5220	15300
Large Size	11	35	16	26	40	4	94774	10192	7520	22080
	12	40	18	28	45	4	117114	12678	8872	26088
	13	45	21	30	50	4	145714	15071	10724	31584
	14	50	23	32	55	4	169216	18665	12468	36780
	15	60	25	35	60	4	221536	24395	15740	46500

6.2 Parameter tuning of the algorithms

The parameter calibration is one of the paramount aspects of evolutionary algorithms which mostly impresses the solution quality and convergence rate of algorithms. Thus, appropriate values of algorithmic parameters are needed to avert the bad simulation results. The standard procedure or theoretical guidelines are rare in the literature for parameter calibration and it typically depends on the practice and capability of scholars. In most of the previous literature, authors have used the trial-and-error method and Taguchi method for parameter calibration. The manual process of parameter calibration using trial-and-error method is difficult. Moreover, it is impractical to investigate all possible parameter combinations (Lam et al., 2012). Hence, in this paper, the parameters of NCRO and NSGA-II are efficiently calibrated using the Taguchi method. This method requires the least number of experiments for tuning compared with the full fractional experimental design. Hence, this technique is more popular for parameter tuning of evolutionary algorithms (Hajipour et al., 2016, Maghsoudlou et al., 2016, Mousavi et al., 2014).

Taguchi method uses the orthogonal arrays to examine the effect of a number of factors on the response variable. Influencing factors are categorized into controllable factors *S* and noise factors *N*. Generally, noise factors cannot be controlled directly. Thus, Taguchi attempts to reduce the effect of noise and to find out the optimal levels of controllable factors. In addition, three objective functions comprising of "smaller is better," "larger is better," and "the nominal is better" are used in Taguchi procedure. The cost and time objective functions of developed model are minimization type, hence in this paper, "smaller is better" is selected. To investigate the performance, the statistical measure called signal to noise ratio *(S/N)* is determined. The response defined by Sarrafha et al., (2015) which is based on the convergence and diversity criteria of the multi-objective problem is used in this paper. This metric is defined by the equation (49).

$$R = MID/SNS \qquad (49)$$

Mean Ideal distance (MID): It measures the convergence rate of the Pareto fronts and can be depicted as follows:

$$\text{MID} = \frac{\sum_{i=1}^{n} c_i}{n}$$

Where $c_i = \sqrt{f_{1i}^2 + f_{2i}^2}$ and n is the number of non-dominated solutions. Therein, f_{1i}, f_{2i} are the value of the i^{th} non-dominated solution for the first and second objective functions. The smaller value of MID provides the better quality solution.

Spread of non-dominance solution (SNS): It is the diversity measure of the Pareto archive solutions. The larger value of SNS is desired for better performance of the algorithm.

$$\text{SNS} = \sqrt{\frac{\sum_{i=1}^{n}\left(MID - c_i\right)^2}{n-1}}$$

Various parameter levels of algorithms are given in Table 5. On the basis of parameters and their levels, L27 and L9 design of Taguchi method are employed for NCRO and NSGA- II algorithm, respectively. Finally, the orthogonal arrays of each design and response (R) obtained through NCRO and NSGA-II are reported in Tables 6 and 7. Moreover, Fig. 9 illustrates the effect plot of the *S/N* ratio for each algorithm. The best levels of all the parameters of each algorithm are selected using the results of the main effect plot of *S/N* ratio. Thus, the appropriate values of the parameters are highlighted in Table 5. The termination criteria of a maximum number of iterations (Max iteration = 200) has been set for proposed algorithms for all experiments.

Table 5 Algorithm parameter ranges along with their levels

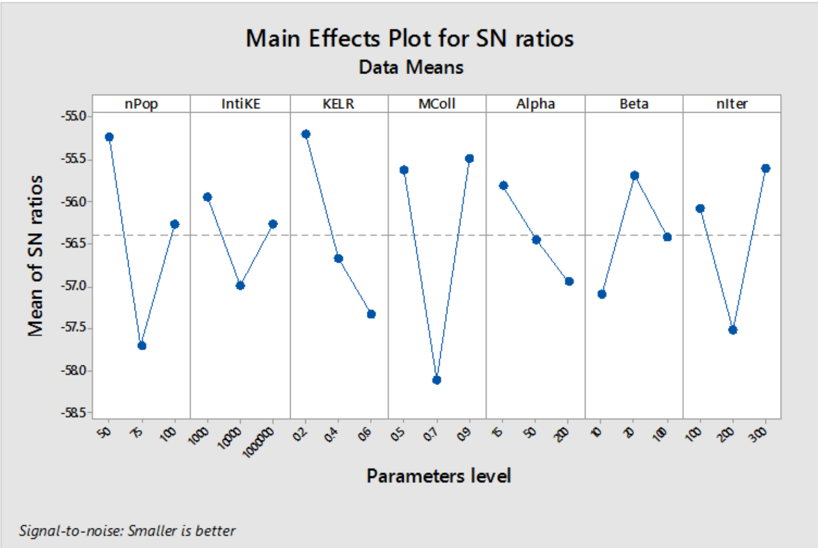
Multi-objective algorithms	Algorithm parameters	Parameters range	Low	Medium	High
NCRO	nPop	50-100	50	**75**	100
	InitialKE	1000-1000000	1000	**10000**	1000000
	KELossRate	0.2-0.6	0.2	0.4	**0.6**
	MoleColl	0.5-0.9	0.5	**0.7**	0.9
	DecThres	15-200	15	50	**200**
	SynThres	10-100	**10**	20	100
	nIter	100-300	100	**200**	300
NSGA-II	nPop	50-100	50	**75**	100
	Pc	0.85-0.95	0.85	**0.9**	0.95
	Pm	0.05-0.15	0.05	**0.1**	0.15
	nIter	100-300	100	**200**	300

Table 6 Obtained response values of NCRO

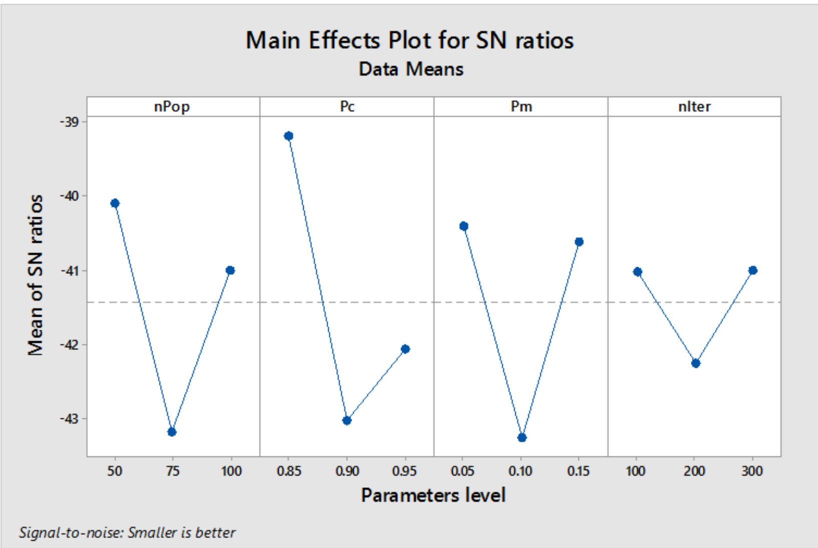
Run order	Algorithm parameters							Response Value		
	nPop	InitialKE	KELossRate	MoleColl	DecThres	SynThres	nIter	MID	SNS	R
1	50	1000	0.2	0.5	15	10	100	418541.02	1076.68	388.73
2	50	1000	0.2	0.5	50	20	200	419009.94	977.82	428.51
3	50	1000	0.2	0.5	200	100	300	418757.09	841.64	497.55
4	50	10000	0.4	0.7	15	10	100	418750.25	542.98	771.21
5	50	10000	0.4	0.7	50	20	200	419727.42	508.09	826.08
6	50	10000	0.4	0.7	200	100	300	418041.27	572.72	729.92
7	50	1000000	0.6	0.9	15	10	100	418748.29	703.46	595.27
8	50	1000000	0.6	0.9	50	20	200	418779.38	657.91	636.53
9	50	1000000	0.6	0.9	200	100	300	419171.66	860.40	487.18
10	75	1000	0.4	0.9	15	20	300	419133.73	1241.14	337.70
11	75	1000	0.4	0.9	50	100	100	419001.30	683.70	612.84
12	75	1000	0.4	0.9	200	10	200	417991.42	279.98	1492.92
13	75	10000	0.6	0.5	15	20	300	417486.02	516.33	808.57
14	75	10000	0.6	0.5	50	100	100	419050.31	376.90	1111.84
15	75	10000	0.6	0.5	200	10	200	419947.83	649.01	647.06
16	75	1000000	0.2	0.7	15	20	300	419203.20	523.15	801.31
17	75	1000000	0.2	0.7	50	100	100	417364.34	683.39	610.72
18	75	1000000	0.2	0.7	200	10	200	418739.19	399.42	1048.37
19	100	1000	0.6	0.7	15	100	200	418362.79	423.22	988.52
20	100	1000	0.6	0.7	50	10	300	418610.46	574.99	728.03
21	100	1000	0.6	0.7	200	20	100	418683.42	517.58	808.92
22	100	10000	0.2	0.9	15	100	200	419217.13	648.66	646.28
23	100	10000	0.2	0.9	50	10	300	419068.87	705.58	593.94
24	100	10000	0.2	0.9	200	20	100	419519.90	993.66	422.20
25	100	1000000	0.4	0.5	15	100	200	419080.79	807.13	519.22
26	100	1000000	0.4	0.5	50	10	300	418822.35	670.47	624.67
27	100	1000000	0.4	0.5	200	20	100	419239.30	614.65	682.08

Table 7 Obtained response values of NSGA-II

Run order	Algorithm parameters				Response Values		
	nPop	Pc	Pm	nIter	MID	SNS	R
1	50	0.85	0.05	100	416376.51	6265.36	66.46
2	50	0.90	0.10	200	416573.97	2526.68	164.87
3	50	0.95	0.15	300	419763.44	4454.76	94.23
4	75	0.85	0.10	300	412721.87	3150.03	131.02
5	75	0.90	0.15	100	414047.82	2754.62	150.31
6	75	0.95	0.05	200	415698.41	2740.37	151.69
7	100	0.85	0.15	200	419418.08	7373.69	86.06
8	100	0.90	0.05	300	412271.61	3617.15	113.98
9	100	0.95	0.10	100	410421.23	2890.20	142.00



NCRO



NSGA-II

Fig. 9. The mean *S/N* ratio plot for each algorithm

6.3 Computational results

In order to solve and validate the formulated model, the proposed algorithms are coded in MATLAB R2014a software environment. Furthermore, all the experiments are performed on a workstation with the configuration of Intel Core i5, 2.90 GHz processor with 8 GB RAM. Firstly, the NCRO algorithm with best parameter levels from Table 5 is utilized to solve all 15 generated problem instances. Meanwhile, to validate the solution obtained through NCRO, another robust MOEA called NSGA-II with calibrated parameter values was implemented. Each problem instance is solved using NCRO and NSGA-II algorithm and computational results of 20 runs are mentioned in Table 8. The total costs (INR), total lead time (hours) and computational time (seconds) of algorithms are determined by taking the mean of 20 runs of the algorithm. The total number of base and field silos established along with their types for all the problem instances are portrayed in the last two columns of Table 8. It has been observed from the result that established base and field silos are more of small size, then medium size and finally large size. The major share of transportation cost in total network cost is the main reason behind this. If we try to focus on minimizing the number of silos to be constructed, then investment cost will be reduced. However, transportation cost will increase due to the less number of silos and this proportional increase in transportation cost will be more than the proportional decrease in fixed cost of silo establishment. Hence, total network cost and total lead time will increase when the less number of silos are established. Moreover, the Pareto front obtained through NCRO algorithm of selected one instance from each category is compared to the Pareto front of NSGA-II algorithm in Figs 10 (a), (b) and (c). As per the results of Table 8, the total cost obtained through NCRO algorithm is lower than those attained using NSGA-II for all problem instances. Pertaining to the second objective of lead time minimization, NCRO provides the better results compared to the NSGA-II algorithm. The smaller computational time is taken by the NCRO meta-heuristic than NSGA-II to solve each problem instance depicts the superiority of NCRO over the NSGA-II. Moreover, two measures including MID and SNS clearly illustrates the better performance of the proposed algorithm. The NCRO algorithm provides better results than the NSGA-II due to the following promising features. The NCRO uses a Q-NDSA procedure which requires the less number of comparisons for sorting of the population compared to the NSGA-II. Therein, a pre-defined function based on rank and crowding distance is used to sort the population based on potential energy. The better convergence of NCRO algorithm is ensured by two local search operators including on wall ineffective and intermolecular ineffective collision. Furthermore, a good diversity performance of NCRO is observed due to its ability of well-controlling the trade-off between intensification and diversification using its four operators and control of search direction through kinetic energy. The NCRO avoids the visiting of non-promising regions in the solution search space due to the potential energy management rules.

The sufficient alternatives need to be provided to the decision makers to choose among the several trade-off solutions by balancing the objectives because of their conflicting nature. In the multi-objective problem, the Pareto front provides the set of non-dominated solutions and decision makers select the best compromise solution according to the company requirement. In this paper, many trade-off solutions are obtained after solving the model using the proposed two algorithms as shown in Figs 10 (a), (b) and (c). As per the preferences of GOI/FCI, they can choose the best compromise solution from the obtained multiple non-dominated solutions. If they give higher preference to the total network cost, then the compromise solution with lowest total network cost will be selected. However, the corresponding value of total lead time will be very high and vice-versa. In the present situation, the good compromise solution among the set of Pareto optimal solutions as shown in Figs 10 (a), (b) and (c) (marked with the black circle) is selected by properly balancing the total network cost and total lead time. The Pareto front preserves the convergence and diversity features of multi-objective nature of the problem.

Table 8 The solutions obtained by NCRO and NSGA-II for 15 problem instances

Problem number	Problem instance (P-B-F-D-T)	NSGA-II			NCRO			Number of base silo constructed (their types)	Number of field silo constructed (their types)
		Total network cost (INR)	Total lead time (hr)	CPU time (s)	Total network cost (INR)	Total lead time (hr)	CPU time (s)		
1	(5-3-4-7-2)	6.31×10^9	2.10×10^5	44.28	5.51×10^9	1.74×10^5	26.83	2 (s = 1, m = 1, l= 0)	3 ($\hat{s}=0,\ \hat{m}=1\ \ \hat{l}=2$)
2	(8-4-5-10-2)	1.22×10^{10}	3.29×10^6	130.77	1.08×10^{10}	2.86×10^6	81.48	2 (s = 1, m = 1, l= 0)	4 ($\hat{s}=2,\ \hat{m}=1\ \ \hat{l}=1$)
3	(10-5-8-13-2)	1.63×10^{10}	5.64×10^6	219.84	1.44×10^{10}	4.29×10^6	175.82	4 (s = 1, m = 2, l= 1)	7 ($\hat{s}=4,\ \hat{m}=2\ \ \hat{l}=1$)
4	(12-6-10-15-2)	2.15×10^{10}	5.83×10^6	551.45	2.06×10^{10}	4.98×10^6	452.44	5 (s = 3, m = 2, l= 0)	8 ($\hat{s}=4,\ \hat{m}=4\ \ \hat{l}=0$)
5	(15-8-13-20-2)	2.36×10^{10}	7.62×10^6	1345.45	2.14×10^{10}	7.43×10^6	1051.86	6 (s = 3, m = 2, l= 1)	11 ($\hat{s}=6,\ \hat{m}=3\ \ \hat{l}=2$)
6	(18-10-15-22-3)	3.61×10^{10}	1.44×10^7	2060.27	3.46×10^{10}	1.35×10^7	1616.73	7 (s = 3, m = 3, l= 1)	13 ($\hat{s}=6,\ \hat{m}=5\ \ \hat{l}=2$)
7	(20-11-17-25-3)	3.66×10^{10}	2.17×10^7	2627.35	3.54×10^{10}	1.94×10^7	2302.43	8 (s = 3, m = 3, l= 2)	15 ($\hat{s}=8,\ \hat{m}=4\ \ \hat{l}=3$)
8	(23-13-18-28-3)	4.35×10^{10}	3.59×10^7	2959.04	4.22×10^{10}	3.50×10^7	2658.51	10 (s = 5, m = 4, l= 1)	16 ($\hat{s}=9,\ \hat{m}=5\ \ \hat{l}=2$)
9	(26-14-22-32-3)	4.66×10^{10}	7.14×10^7	3296.47	4.39×10^{10}	6.83×10^7	3008.38	11 (s = 4, m = 5, l= 2)	19 ($\hat{s}=7,\ \hat{m}=9\ \ \hat{l}=3$)
10	(30-15-25-35-3)	4.74×10^{10}	8.06×10^7	3665.88	4.53×10^{10}	7.50×10^7	3309.55	13 (s = 6, m = 5, l= 2)	22 ($\hat{s}=12,\ \hat{m}=7\ \ \hat{l}=3$)
11	(35-16-26-40-4)	5.64×10^{10}	2.13×10^8	4238.19	5.20×10^{10}	1.95×10^8	3960.10	14 (s = 6, m = 6, l= 2)	23 ($\hat{s}=11,\ \hat{m}=8\ \ \hat{l}=4$)
12	(40-18-28-45-4)	5.80×10^{10}	2.42×10^8	4555.76	5.51×10^{10}	2.27×10^8	4205.58	15 (s = 7, m = 5, l = 3)	24 ($\hat{s}=13,\ \hat{m}=6\ \ \hat{l}=5$)
13	(45-21-30-50-4)	6.07×10^{10}	3.64×10^8	4909.44	5.79×10^{10}	3.43×10^8	4518.93	17 (s =9, m = 6, l = 2)	26 ($\hat{s}=10,\ \hat{m}=12\ \ \hat{l}=4$)
14	(50-23-32-55-4)	1.20×10^{11}	4.23×10^8	5364.48	1.04×10^{11}	4.05×10^8	4778.64	18 (s =10, m =5, l = 3)	29 ($\hat{s}=16,\ \hat{m}=8\ \ \hat{l}=5$)
15	(60-25-35-60-4)	1.32×10^{11}	5.11×10^8	6299.66	1.17×10^{11}	4.79×10^8	5628.71	20 (s =12, m =5, l = 3)	32 ($\hat{s}=17,\ \hat{m}=10\ \ \hat{l}=5$)

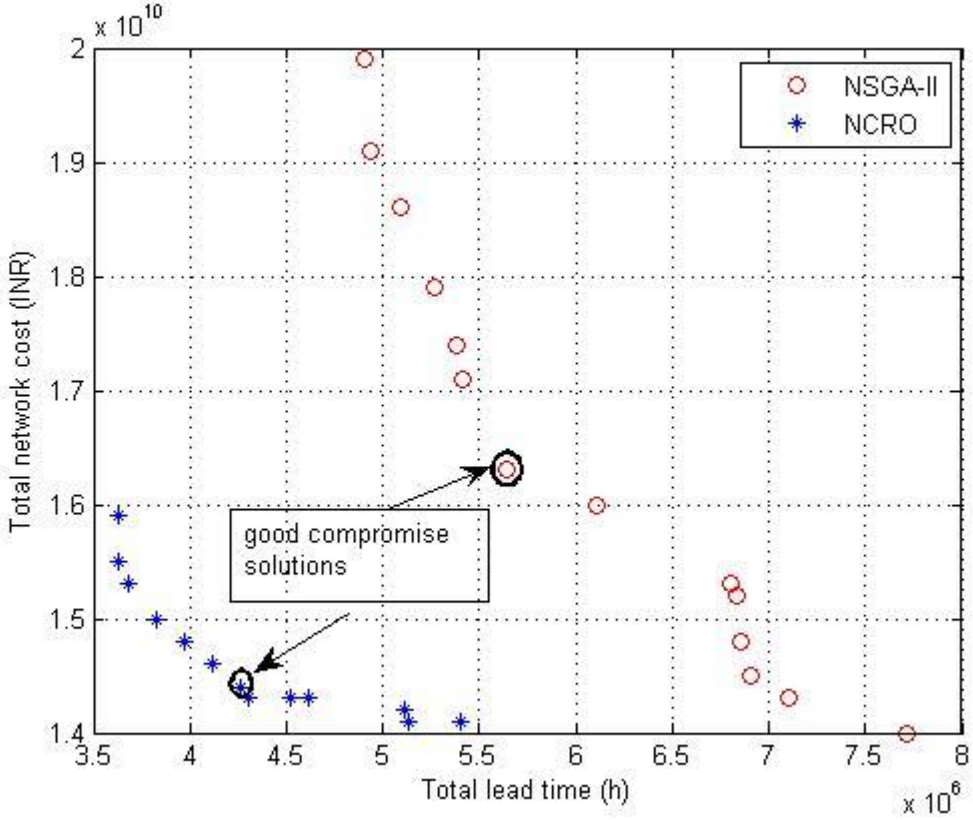


Fig. 10 (a). Obtained Pareto-fronts of the algorithms for problem instance 3

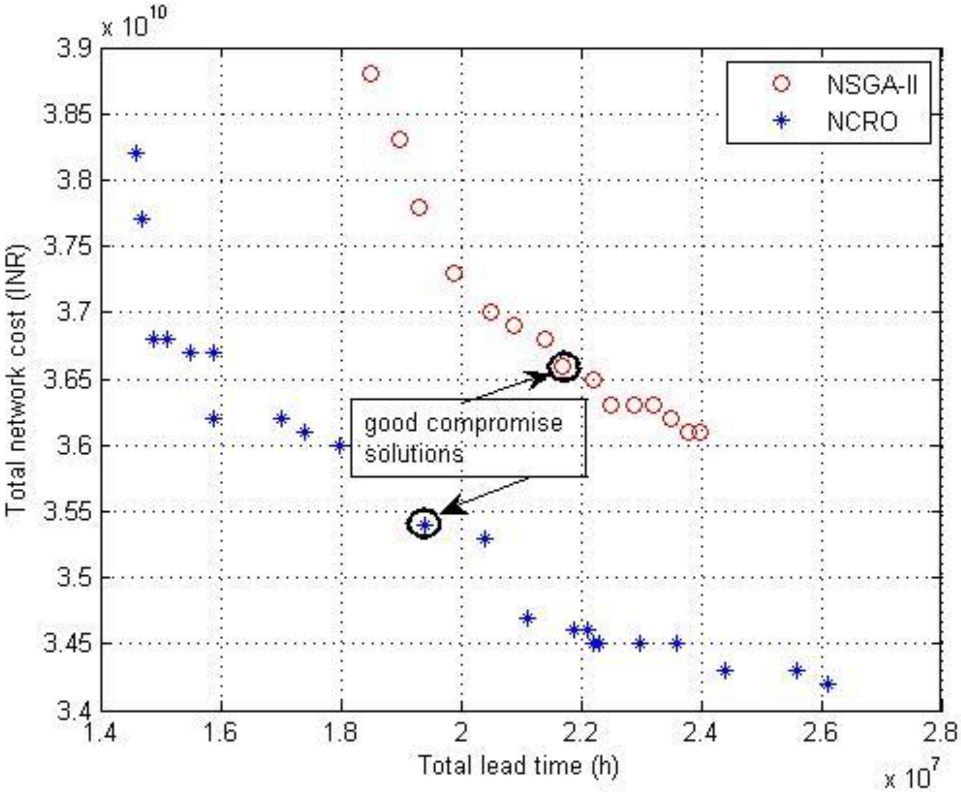


Fig. 10 (b). Obtained Pareto-fronts of the algorithms for problem instance 7

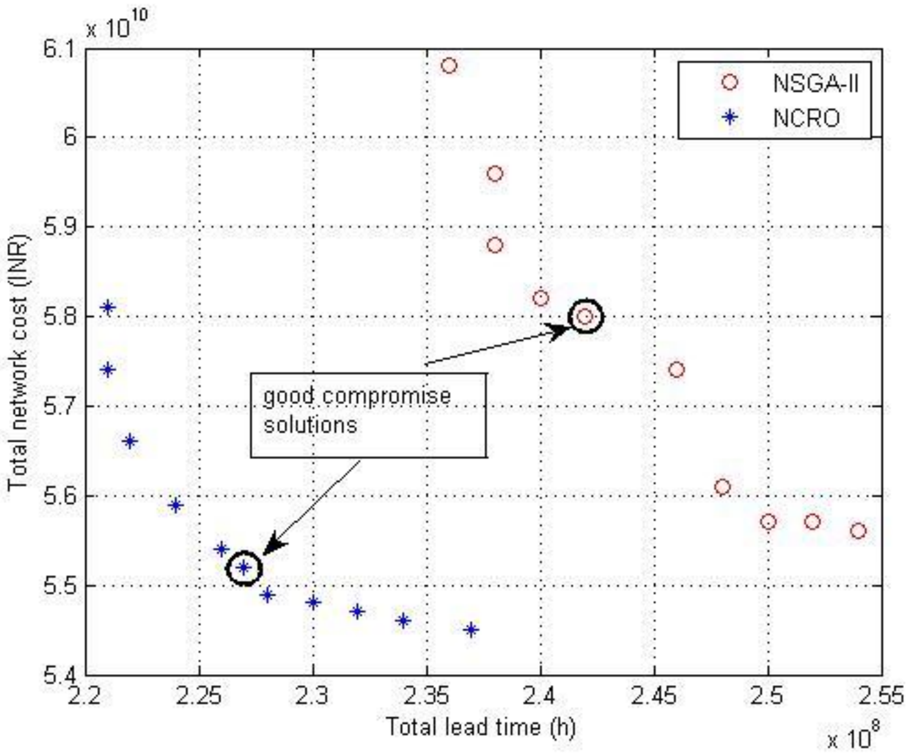


Fig. 10 (c). Obtained Pareto-fronts of the algorithms for problem instance 12

The solution of selected three problem instances in a given finite planning horizon is represented in Figs. 11 (a), (b) and (c). The total food grain quantity transferred between various echelons and inventory stored in a base as well as field silos within a planning period are depicted in Fig. 11 (a). Additionally, Figs. 11 (b) and (c) show the number of each type of vehicles comprising of trucks and rakes utilized in a given planning period on the particular arc. The comprehensive food grain flow and storage analysis of the problem instance 1 for a unit time period has been carried out and shown on the supply chain network flow diagram in Fig. 12. Therein, amount of food grain shipped and a number of each type of vehicles utilized between the various echelons are represented on upper and lower side of each arrow respectively. The mode of food grain transportation is shown by the solid and dotted arrows, where the solid arrow indicates a road and dotted arrow depicts the rail transportation. Mostly, rail transportation is preferred over the road transportation for inter-state movement activities due to long distances, low transportation cost and a huge amount of food grain quantity. The solid base and field silos illustrate that at that potential locations base and field silos are not constructed.

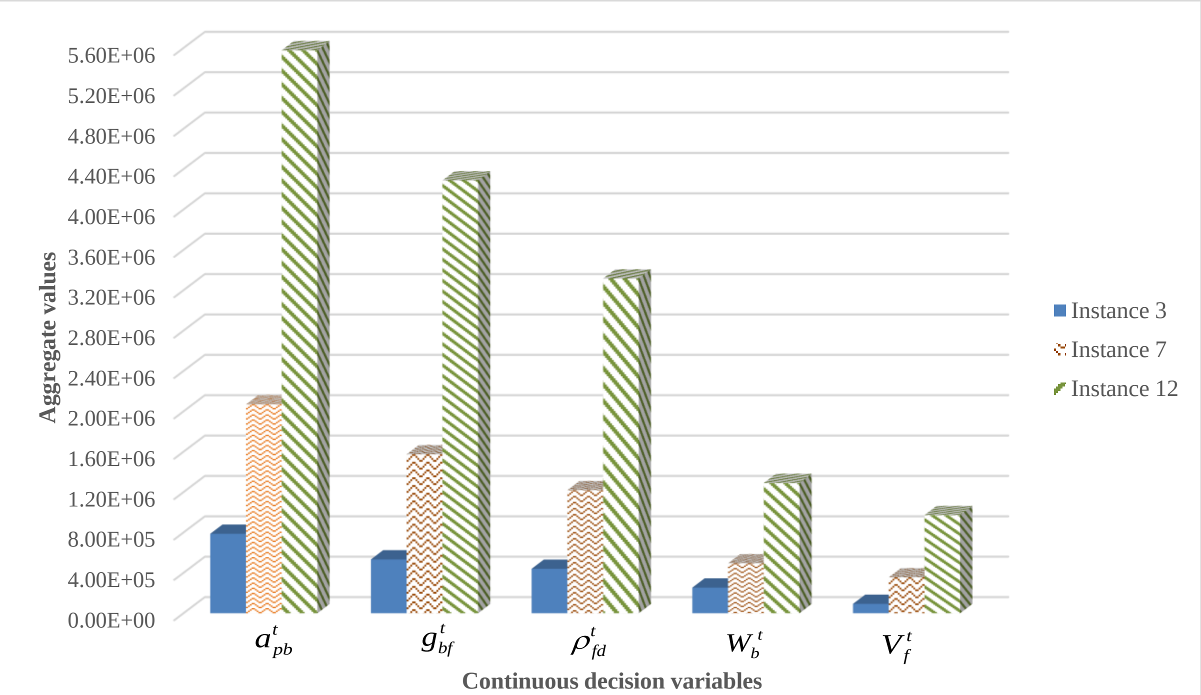


Fig. 11 (a). The aggregate values of food grain quantity transported and inventory at base and field silos

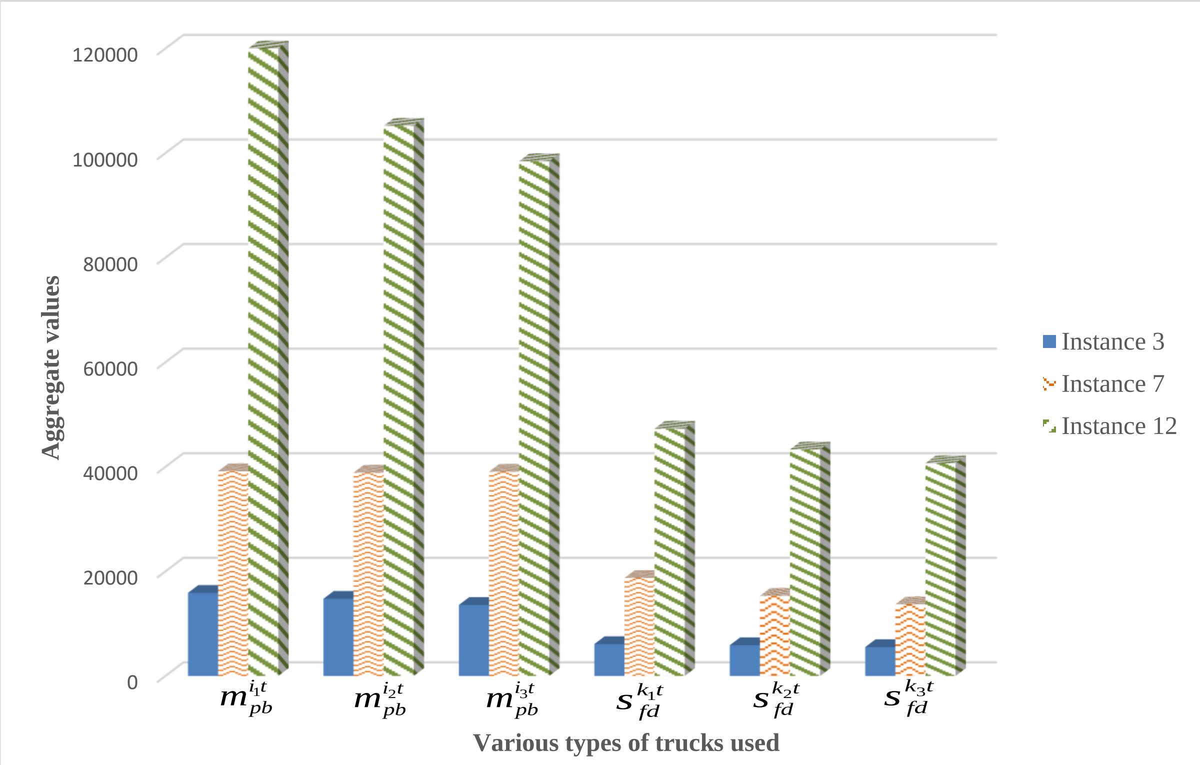


Fig. 11 (b). The aggregate values of various types of trucks used between procurement centres to base silos and field silos to demand points

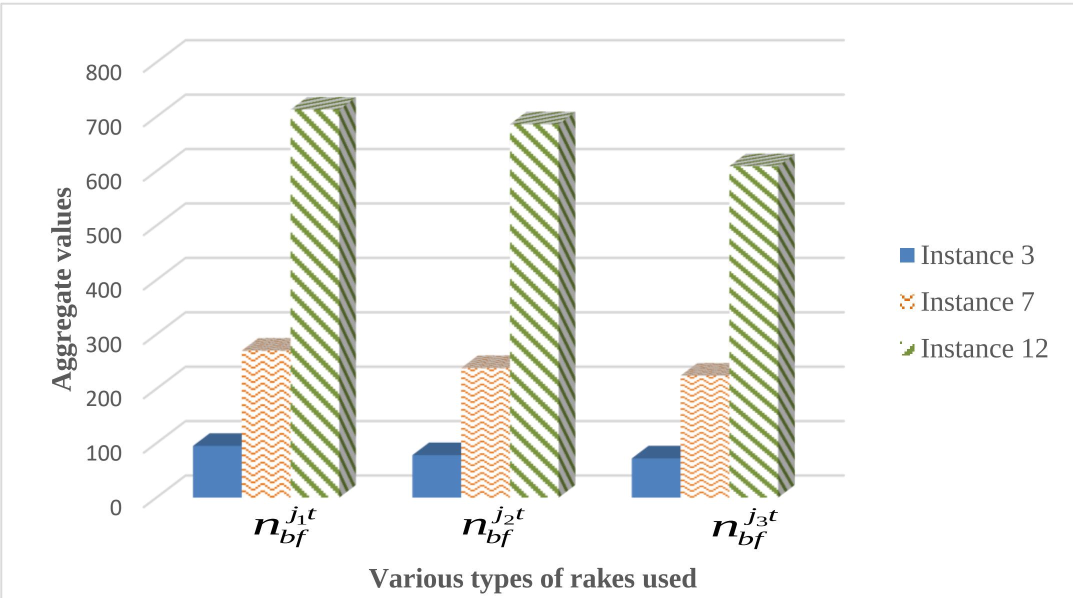


Fig. 11 (c). The aggregate values of various types of rakes used between base silos to field silos

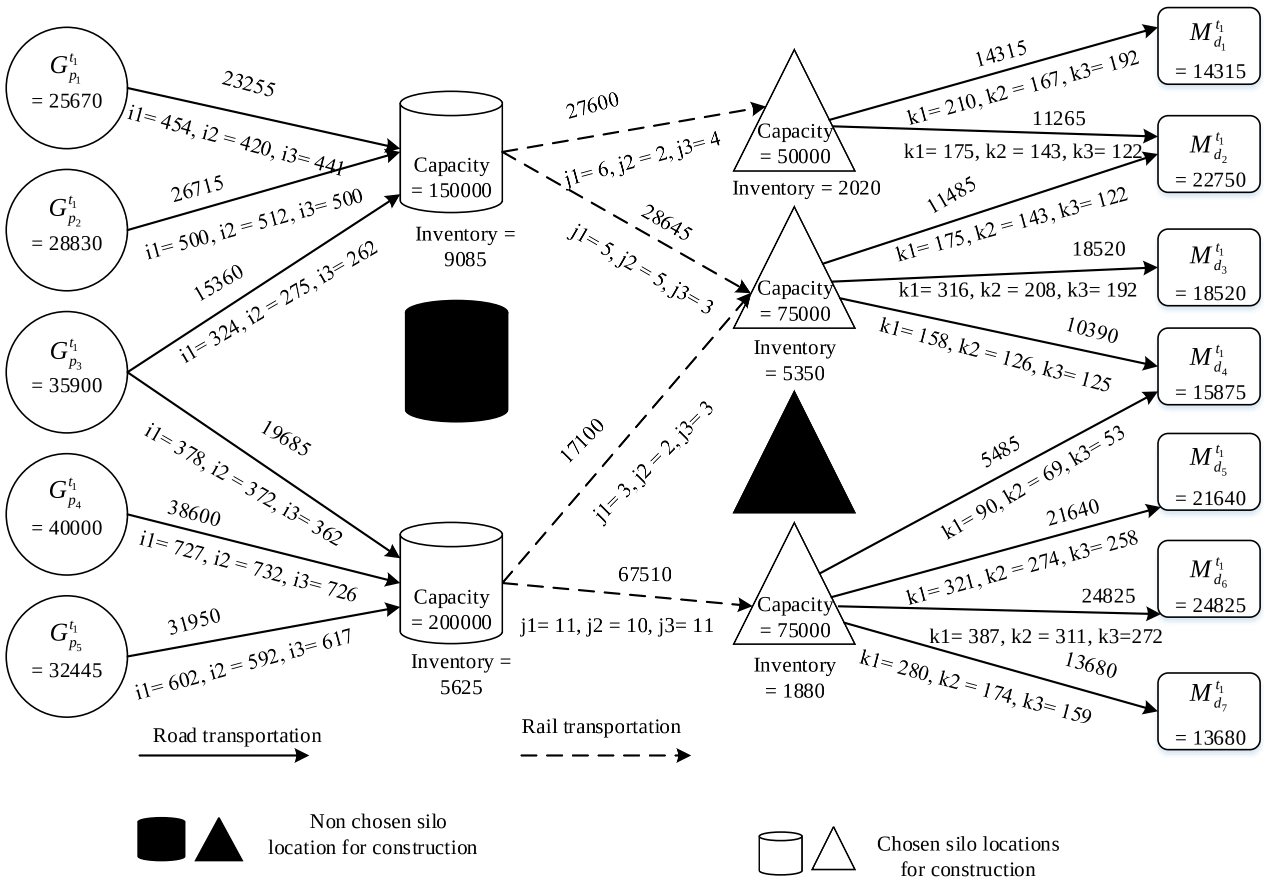


Fig. 12. Food grain flows and vehicles used in a unit time period for problem instance 1

Various components of total network cost and lead time objectives for chosen three instances are depicted in Figs. 13 (a) and (b). The number of base and field silos constructed are also shown on each instance. It can be observed from the Fig. 13 (a) that the major percentage of network cost is the transportation cost, then inventory cost and finally silo construction cost. Similarly, in total lead time objective of Fig. 13 (b), lead time from procurement centres to base silos has the highest portion after that lead time from field silos to demand points and then lead time from base silos to field silos. Finally, dwell time has the least percentage of the total lead time objective. Lead time mainly depends on the number of vehicles used for food grain transportation and if large quantity is moved then more vehicles will be utilized. However, rail-rakes transport the large volume of food grain with less time duration compared with trucks.

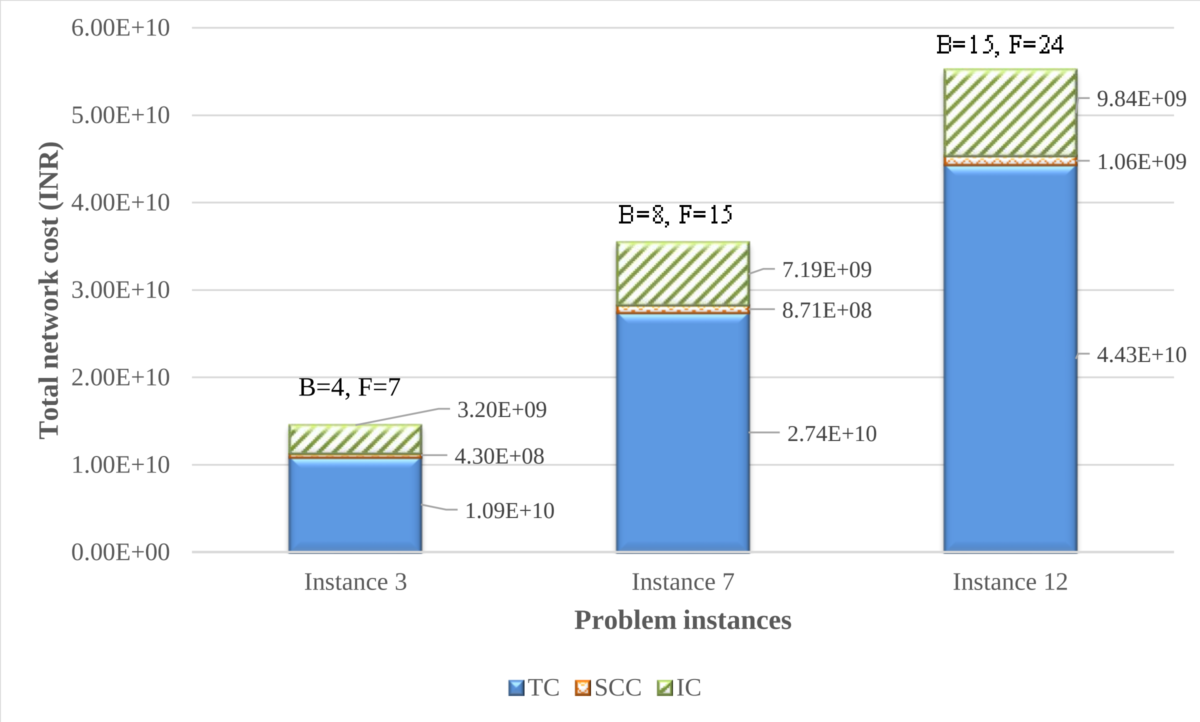


Fig. 13 (a). Total network cost components

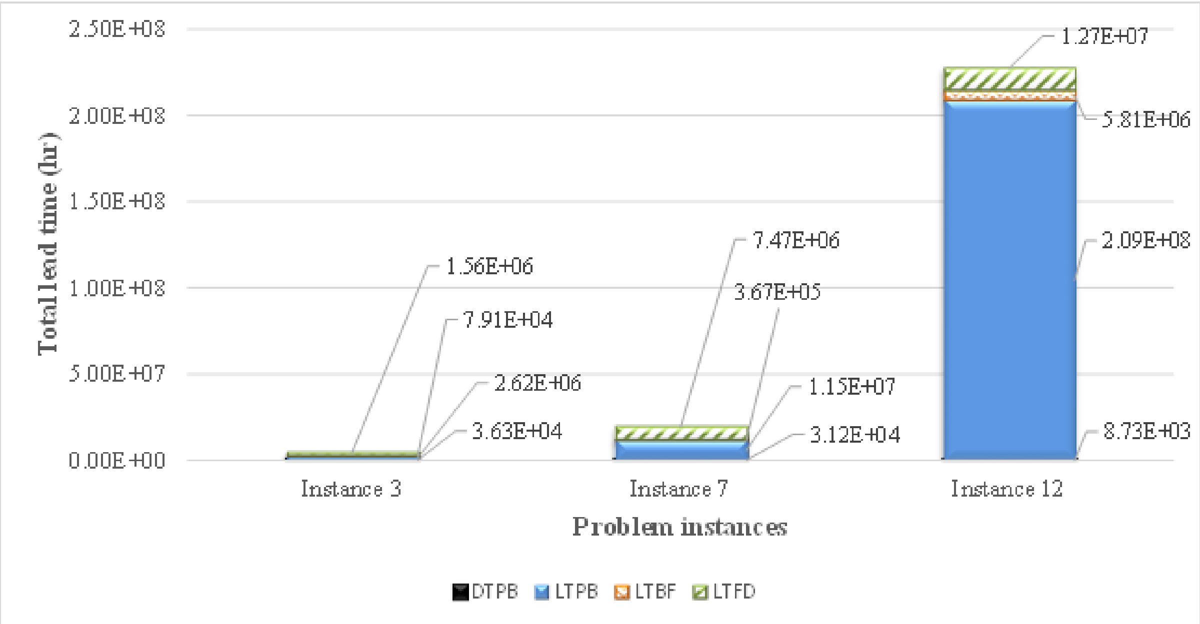


Fig. 13 (b). Total lead time components

6.4 Sensitivity analysis

In order to evaluate the effect of the model parameters on the cost and time objectives and to obtain some insights for FCIs effective decision-making process, the sensitivity analysis has been carried out. The variations of number of procurement centres (*P*), number of demand points (D), the capacity of base and field silos ($\varepsilon_b^q, \varepsilon_f^r$), the fixed cost of base and field silo construction (φ_b^q, c_f^r), transportation cost (α_{pb}) and transit time (τ_{pb}) were considered while performing the sensitivity analysis on the problem instance 3.

6.4.1 The effects of number of procurement centres and demand points

The effect on the cost and time objectives value after varying the number of procurement centers and demand points by -60%, -40%, -20%, +20%, +40%, and +60% from its current values are shown in Figs.14 (a) and (b), respectively. It can be observed from Fig. 14 (a) that as the number of procurement centres increase and decrease by 60% the total cost increases and decreases by 41% and 27% respectively. The value of second objective function i.e. total lead time also increases by 122% and decreases by 45% when the number of procurement centres increase and decrease by 60% due to the variation in a number of vehicles used on the particular arc to transfer the food grain. A similar type of nature of the graph of first and second objective functions with different numerical values is obtained (Fig. 14 (b)) when the demand points are increased and decreased by 60% from their original value. Moreover, the increase or decrease of the number of procurement centres and demand points will also affect the base and field silos to be constructed. This variation in the established base and field silos has been mentioned in Figs. 14 (a) and (b). It can be realized from Fig. 14 (a) that when the number of procurement centres increased by 20%, there is no need for additional base and field silo with respect to the original value. The number of established base and field silos are same when the number of procurement centres decrease by 20%. However, when the number of procurement centres and demand points increase by 40%, then one additional base and field silo are constructed to store more quantity and meet the increased demand and vice-versa.

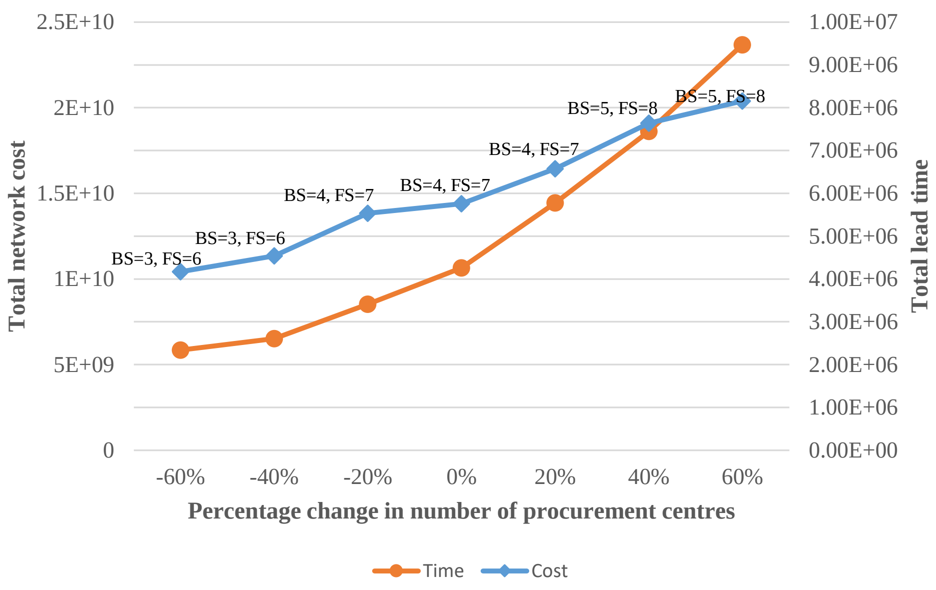


Fig. 14 (a). The effect of variation in number of procurement centres on each objective

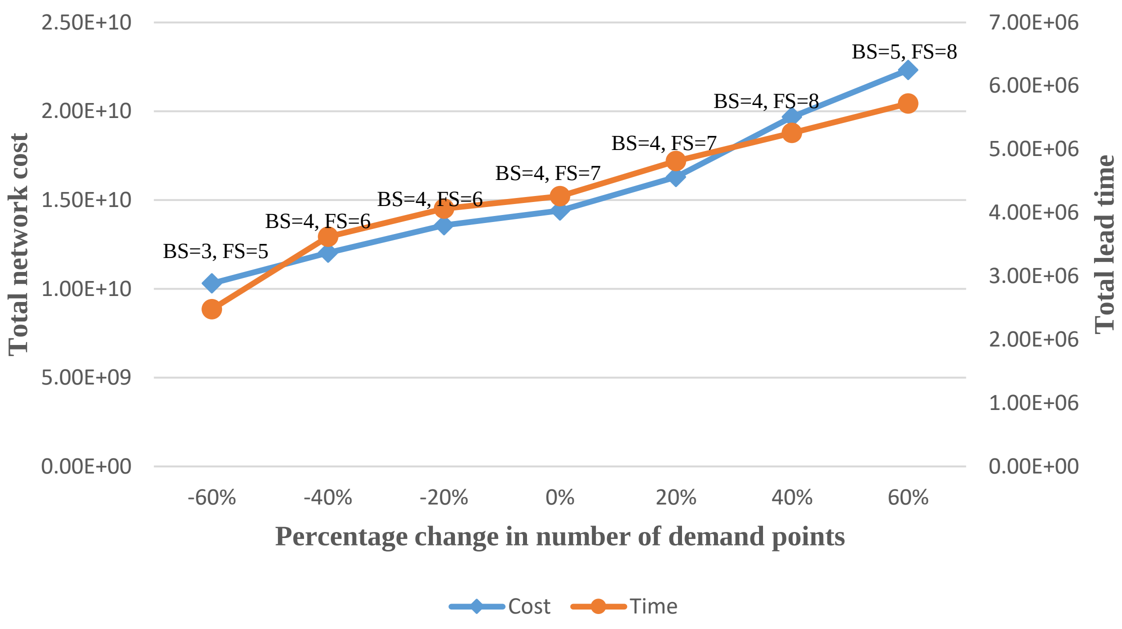


Fig. 14 (b). The effect of variation in number of demand points on each objective

6.4.2 The effects of capacity of base and field silos

Fig. 15 illustrates that increasing the capacity of base and field silos from -60% to 60% of their original value leads to decrease in the total network cost because the proportional increase in fixed silo construction cost is less than the proportional decrease in transportation cost. Furthermore, total lead time will also decrease due to the establishment of new base and field silos.

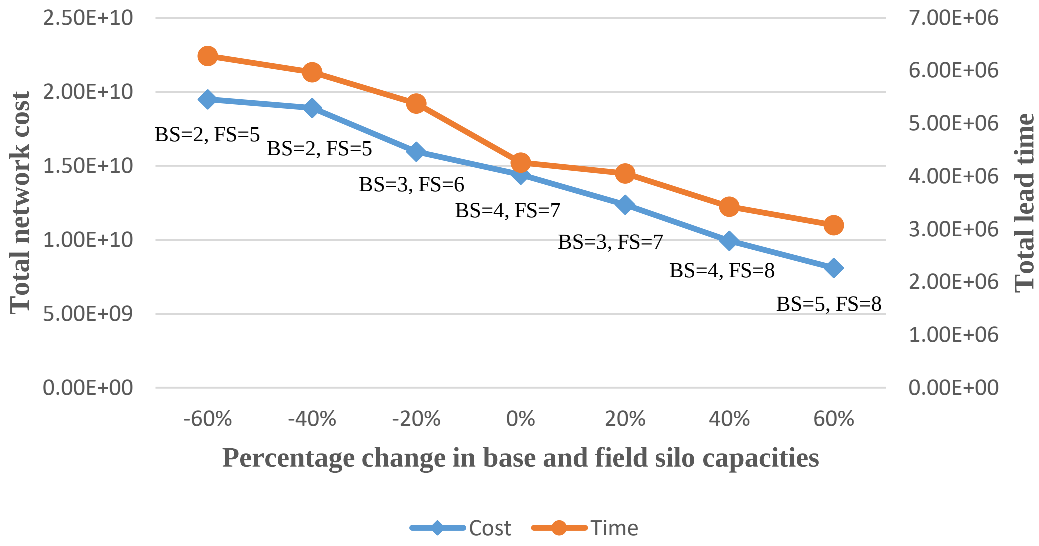


Fig. 15. The effect of variation in base and field silo capacities on each objective

6.4.3 The influence of fixed costs of base and field silo construction

Each type of base and field silo needs the fixed cost of establishment. The sensitivities of the solutions in terms of the number of established base and field silos when the fixed cost of construction changed from -30% to 30% of their current cost is shown in Fig. 16. It can be observed from Fig. 16 that as the fixed cost increases the number of silo constructed decreases, therefore total fixed cost of silo construction decreases. However, transportation cost increases due to the less number of silos and this proportional increase in transportation cost is more than the proportional decrease in fixed cost of silo establishment. Hence, total network cost and total lead time increase when fixed cost increases.

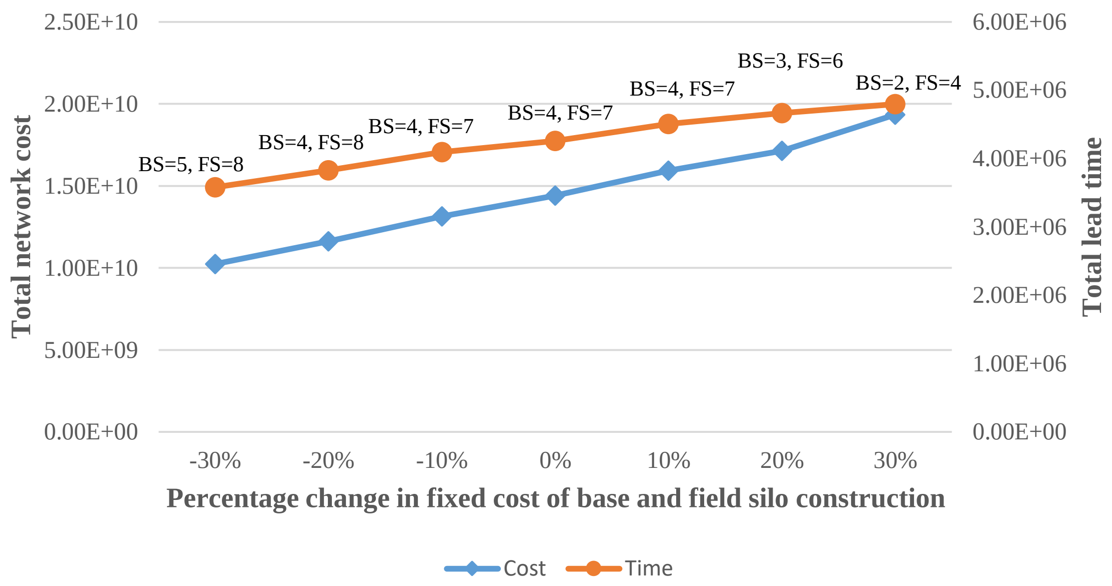


Fig. 16. The influence of fixed costs of base and field silo construction on each objective

6.4.4 The effects of transportation cost and lead time

The transportation cost and lead time from procurement centres to base silos are considered in this scenario. Both parameters are varied from -30% to 30% of their original values and influence on the first and second objectives is depicted in Fig. 17. It can be seen from Fig. 17, that the first objective function value increases and decreases when the unit transportation cost increases and decreases. Furthermore, the second objective function values portray the similar type of nature of the graph after varying the lead time from procurement centres to the base silos from its present value. The lead time is based on the distance which affects the number of established base and field silos. The more number of base silos is to be constructed to reduce the transit time from procurement centres to base silos and this can be observed from Fig. 17.

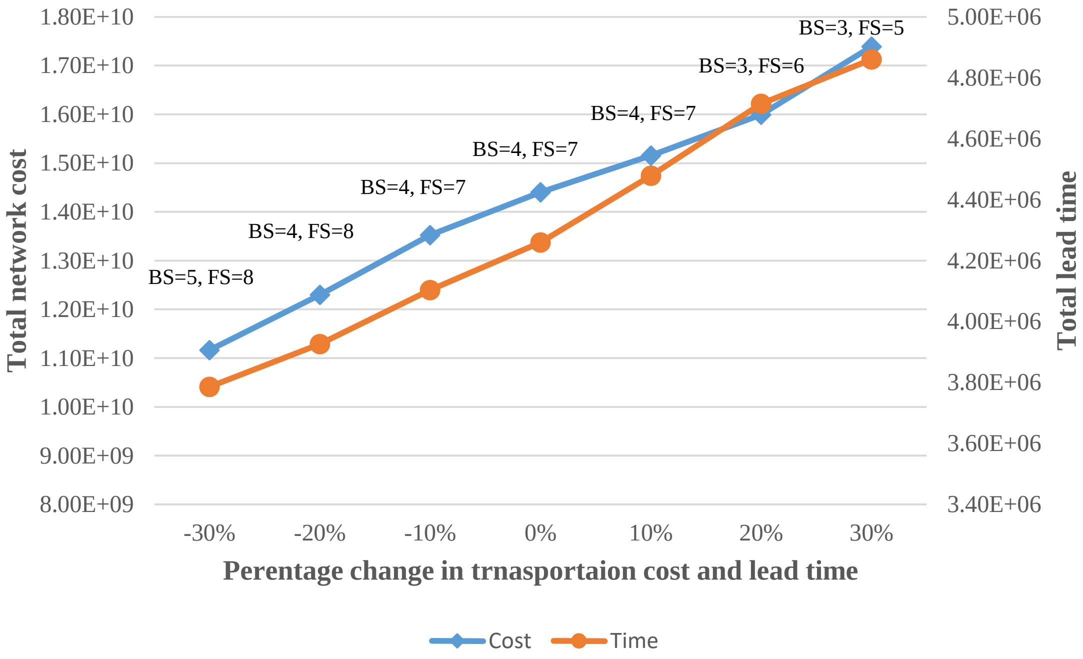


Fig. 17. The effect of variation in transportation cost and lead time on each objective

6.5 Managerial implications and insights

The important few managerial implications which can improve the efficiency and effectiveness of the current food grain supply chain network with respect to results of this study are discussed as follows. Due to the increased central pool stock of food grain and dismal storage capacity addition in the last decade, the GOI should expedite the current silo storage capacity augmentation plan. The transportation cost has the major portion of the total network cost. Therefore, we have to give more focus on transportation cost other than inventory and silo establishment cost while locating the silos. Otherwise, large capacitated silos may be constructed in every state for reducing the investment cost which leads to increase of total network cost. To quickly transfer the food grain from procurement centres to base silos and reduce the post-harvest losses at procurement centres, the available base silos storage capacity and requirement of heterogeneous capacitated vehicles need to be accurately determined. The issue of shortages of rake supply by Railways against the FCI requirement should be addressed as the transportation cost plays a major role in the total network cost. Additionally, small size field silos can be constructed at a district level warehouse in deficit states and packaging facility is to be provided at that location. The cost, time and post-harvest losses of food grain can be reduced by proper planning and management of silo location-allocation decisions across the country.

The valuable and crucial managerial insights obtained through this study would be beneficial to the various officials of the FCI, SGAs, Railways and other private entities involved in the food grain supply chain. The best optimal locations for construction of the different capacitated base and field silos in producing and consuming states can be determined using this model. In order to avoid the huge loss of investment and minimize the lead time of shipment, the GOI can utilize this model for feasibility analysis of different potential locations. In addition, the results of the current study will be helpful for effectively taking the other important decisions comprising of allocation of procurement centres and demand points to different silos, movement of food grain between various echelons and optimal inventory level at the silos. The developed model determines the number of vehicles used for food grain transportation which can solve one of the major issues of shortages of vehicles through proper planning and coordination between FCI, Railways and private contractors. The sufficient availability of vehicle resources and silo capacities can reduce the dwell as well as transit time of food grain shipment which leads to the reduction of food grain losses. Furthermore, the vehicle scheduling which can diminish the demurrage charges of the vehicle will be easily done at every stage of food gain supply chain network using the timely movement plan. The storage activity plan will be helpful for resolving the issue of underutilization of existing storage facilities.

7. Conclusion and future scope

The GOI has started constructing the different capacitated base and field silos in the various surplus and deficit states because of the shortfall of storage capacity with FCI. Lead time including waiting time of food grain in SGAs warehouses is high owing to lack of storage capacity. Thus, food grain losses and carry-over charges are continuously increasing. In this paper, a grain silo location-allocation problem of the Indian food grain supply chain has been addressed by considering the four-echelons including procurement centres, base silos, field silos and demand points. In order to support the decision making process of GOI, a novel MINLP model is formulated with two conflicting objectives - minimization of total supply chain network cost and total lead time. The various factors such as fixed establishment cost, transportation cost, inventory cost, dwell time and transit time are considered in the model. The aim of this study is to determine the optimal locations for establishment of base and field silos in surplus and deficit states along with their capacities. Moreover, food grain flow and inventory level are also determined using the formulated model. A novel dwell time function is developed for waiting time evaluation by taking into account the administrative activity time, vehicles movement from procurement centres to base silos and availability of base silos storage capacity.

Due to the non-linear nature and high complexity of the model, the recently developed multi-objective Pareto-based algorithm called NCRO has been employed for simultaneously optimizing the two conflicting objectives and obtained results are validated using robust NSGA-II algorithm. Further, the Taguchi method was implemented for parameter tuning of NCRO and NSGA-II algorithms. The mathematical model along with solution approach has been verified and validated by solving 15 problem instances considering major surplus and deficit states in India. The superior performance of the NCRO algorithm than NSGA-II, in terms of two multi-objective measures comprising of MID and SNS, two objective function values, computational time and Pareto fronts, is clearly observed through the computational results of several different problem instances. The solution in the form of aggregate values of the various types of decision variables of selected three problem instances and extensive food grain flow along with storage analysis of problem instance 1 for a single period is reported in computational results subsection. According to the computational experiments, transportation cost contributes significantly to the total network cost, then inventory cost and lastly silo establishment cost. Therefore, more number of small size, then medium size and finally large size base and field silos are selected for construction. Finally, the influence of some model parameters like procurement centres, demand points, capacity and fixed cost of base and field silos, etc. on the cost and time objectives as well as on established base and field silos is examined through sensitivity analysis approach. The insights evolved through this study will be advantageous to the various officials of the GOI/FCI, SGAs and other entities engaged in the food grain supply chain for their planning and coordination decisions. The feasibility analysis of various potential locations can be performed through the proposed model.

In the current work, a sensitivity analysis was conducted to examine the impact of uncertain parameters on solution quality. Future study can incorporate the stochasticity in model parameters including demand, procurement and transportation time such that obtained solutions can optimize the expected values of objective functions. The development of fuzzy multi-objective model will be another possible extension of the current study. Furthermore, the inclusion of backlog and shortages can make the model more realistic according to the suitability of the problem environment. In order to implement the current model, the set of potential locations of base and field silos must be known. However, in some cases, FCI may require the support for the determination of appropriate potential locations. The different capacity levels of silos can be relaxed in the future study. In the context of sustainability, the minimization of carbon emission can be considered as a third objective in addition to the cost and time.

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