Modelling of sustainable food grain supply chain distribution system: a bi-objective approach

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Abstract: Growing food demand, environmental degradation, post-harvest losses and the dearth of resources encourage the decision makers from developing nations to integrate the economic and environmental aspects in food supply chain network design. This paper aims to develop a bi-objective decision support model for sustainable food grain supply chain considering an entire network of procurement centres, central, state and district level warehouses, and fair price shops. The model seeks to minimize the cost and carbon dioxide emission simultaneously. The model covers several problem peculiarities such as multi-echelon, multi-period, multi-modal transportation, multiple sourcing and distribution, emission caused due to various motives, heterogeneous capacitated vehicles and limited availability, and capacitated warehouses. Multiple realistic problem instances are solved using the two Pareto based multi-objective algorithms. Sensitivity analysis results imply that the decision makers should establish a sufficient number of warehouses in each producing and consuming states by maintaining the suitable balance between the two objectives. Various policymakers like Food Corporation of India, logistics providers and state government agencies will be benefited from this research study.

Keywords: Food supply chain; Sustainable supply chain; Facility location; Transportation; Modelling and optimization

1. Introduction

1.1 Background

Global food demand is estimated to increase by 50% by 2030 which leads to upsurge the demand of resources for production and transportation (Allaoui et al. 2018, Bruinsma 2017). Globally, around 1.3 billion tons of total food produced is wasted or lost annually (Gustavsson et al. 2011; FAO 2013). The food production in India has been steadily augmented thanks to advanced agricultural production technologies, but the food losses are still one of the major issues (Sharon et al. 2014; Kumar and Kalita 2017; Parwez 2014). Approximately 30-35% of the total food produced is wasted annually because of insufficient infrastructure and ineffectual supply chain (Parwez 2014; Comptroller and Auditor General of India (CAG) report 2013). Various inputs containing land, water, pesticides, fertilizer, and energy are required for producing food. The process leads to the production of greenhouse gas emissions. Therefore, wastages of resources and production of emissions are two main consequences of food losses (FAO 2013; Zhu et al. 2018). Additionally, food loss is one of the major causes of significant environmental impact along with economic and social impacts (Dreyer et al. 2019; Lemaire and Limbourg 2019; Scholz et al. 2015).

Transportation planning is one of the vital element in the total costs of any supply chain (Maiyar and Thakkar 2017; Song et al. 2014). India comes third after China and the US in the largest global greenhouse gases emitter ranking (Timperley 2019). Also, transportation activities are the major causes of air pollution which have harmful effects on human health (Kelle 2019; Wang et al. 2011). Globally freight transport typically contributes 80-90% for transportation-related carbon-emission (McKinnon 2010). In 2018, transportation activities emitted 24% of the world's annual carbon dioxide (Teter et al. 2019). Road transportation emission is the major contributor (94.5%) for India's total transport sector emission of 261 tons of CO_2 (Shrivastava et al. 2013). Further, the agricultural sector has a share of 16% in total greenhouse gas emissions (Timperley 2019). The crop yield in India is considerably reduced because of the heightened air pollution and climatic factors (Burney and Ramanathan 2014). Therein, approximately 5 million tons of crops (wheat and rice) get damaged annually due to pollutant gases (Ramanathan et al. 2014). According to the report of the Lancet Commission on pollution and health, India has ranked at first position in pollution-related deaths (2.51 million deaths in 2015) (Landrigan et al. 2018). Therefore, consideration of the environmental impact of Food Supply Chain (FSC) activities along with the economic impact is very imperative and it increases the problem complexity (Banasik et al. 2019; Mohammed and Wang 2017b; Seuring 2013; Brandenburg et al. 2014; Wang et al. 2019).

1.2 Indian food grain supply chain distribution system

This study is related to the food grain supply chain of Public Distribution System (PDS) in India as shown in Figure 1. Under the PDS, the Food Corporation of India (FCI) distributes the subsidized food grains to the weaker and vulnerable section of society (CAG, 2013; Mogale et al. 2018). Procurement from farmers, storage, transportation and distribution to final consumers through Fair Price Shops (FPS) are major activities of FCI (Maiyar et al. 2015). Due to the mismatch between the supply and demand of particular states, food grain has to be transferred from producing (surplus) states to consuming (deficit) states (Maiyar and Thakkar 2017; Mahapatra and Mahanty 2018; Balani et al. 2013). The major wheat producing and consuming states in India are situated in a large geographically dispersed area, which results in more fuel consumption for food grain transportation (Reddy et al. 2017; Anoop et al. 2018, High-level committee report (HLC) 2015). The food grain is transported from surplus to deficit states through rail mode to meet the demand of the people (CAG 2013; Maiyar et al. 2015; Mogale et al. 2017; Balani et al. 2013).

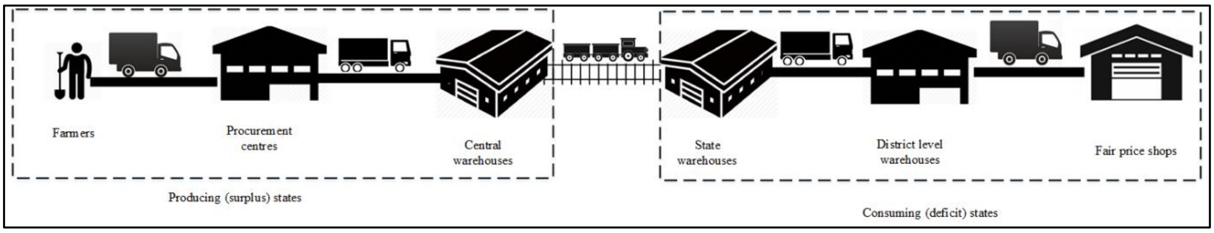


Figure 1. Indian food grain supply chain distribution system

1.3 Motivations

The key motivations behind the current study including food grain storage problems, improper planning and coordination issues are realized from the CAG report (2013), HLC report (2015) and online sources (Indiastat). According to these sources, the total food grains stock in the central pool has progressively augmented from 21 Million Metric Ton (MMT) in 2007 to 66.78 MMT in 2012, whereas FCI has increased its owned storage capacity by merely 0.4 MMT (15.2 – 15.6 MMT) in the period from 2006-07 to 2011-12. The shortfall in storage capacity with FCI against the required capacity indicates an increasing trend from 5.99 MMT in 2007-08 to 33.18 MMT in 2011-12. These statistics indicate the discrepancy between the available storage capacity and central pool stock and emphasize the requirement of more storage capacity to deal with escalating procurement. Furthermore, the CAG report revealed severe disparities in the availability of storage capacity and a colossal dearth of storage space in deficit states. The abrupt augmentation of food grains stock in the central pool impels the concern of larger movement from producing to consuming states. In order to bridge the storage capacity gap, policymakers in India are establishing the heterogeneous capacitated warehouses in surplus and deficit states. Annually, on an average of 40 to 42 million tons of food grains are transferred across the country using the road, rail, and waterways (http://fci.gov.in). According to the CAG 2013 report, the total number of 10,969 rakes are dispatched for food grain movement during the period of 2011-12. Managing the food supply chain is an intricate and difficult issue since the number of intermediaries may differ from a commodity to another and to a country to another (Sachan et al. 2005; Higgins et al. 2010; Piramuthu et al. 2013). The post-harvest activities including transportation, processing, and storage are responsible for producing emissions (Allaoui et al. 2018; Banasik et al. 2019; FAO, 2013).

1.4 Major contributions

The main contributions of this paper are as follows. Firstly, a new bi-objective mathematical model is formulated for integrated sustainable food grain supply chain distribution system considering an entire network of procurement centres, central, state and district level warehouses, and fair price shops. The objectives of the model are the minimization of cost and carbon dioxide emissions. Moreover, the model introduces several practical and realistic features of the problem like multiple echelons, periods, transportation modes, sourcing and distribution along with heterogeneous capacitated vehicles and their limited availability. Transportation emissions affected by vehicle types, load of vehicles and travelled distances, emission caused due to facility establishment, holding and handling operations are also incorporated in the proposed model. Additional characteristics such as geographically dispersed producing and consuming states, capacitated warehouses and vehicle capacity restrictions are integrated into the model. The developed model supports the policymakers in strategic and tactical planning decisions by optimizing the facility establishments, inventory level, and food grain flow from procurement centres to fair price shops. Furthermore, several trade-off solutions are obtained by solving the model using two Pareto based multi-objective algorithms namely, Multi-objective Particle Swarm Optimization (MOPSO) and Non-Dominated Sorting Genetic Algorithm (NSGA-II).

1.5 Structure of the paper

The remainder of the paper is organized in the following way. In Section 2, relevant literature is discussed. Section 3 presents the underline problem description. The formulation of the mathematical model is described in Section 4. In Section 5, the research methodology is explained. Section 6 is devoted to the results and discussion. Finally, concluding remarks, implications and future scope are given in Section 7.

2. Review of relevant literature

Recently, an interesting and insightful mathematical model-oriented review of the extant literature focusing on Sustainable Food Supply Chain (SFSC) domain was conducted by Esteso et al. (2018) and Zhu et al. (2018). They clearly highlighted the need for the development of mathematical programming models to support the decision making process of FSC in developing countries. The different challenges starting from farmers to consumers, recent trends and topics in FSCs, configuration of FSCs, need of sustainability, integration of the inherent characteristics and network of FSC are discussed in these two papers. They also found that most of the previous authors considered the generic FSC and not explored all the entities involved in it. The necessity of multiple time periods, integration of procurement, transportation and storage decisions, economic and environmental aspects and their conflicting nature, multi-objective modelling and algorithms/heuristics applications are delineated in the aforementioned articles. In addition to this, interested readers can refer the Soto-Silva et al. (2016), Ahumada and Villalobos (2009), Resat and Turkay (2019), Brandenburg and Rebs (2015), Dekker et al. (2012), Demir et al. (2014) and Eskandarpour et al. (2015) for literature review on sustainable supply chain network design and green logistics related aspects. In this section, the relevant literature concentrating on sustainable facility location inventory transportation problem in the FSC domain is discussed. Therein, we mainly focused on various types of models and their characteristics along with different solution methods reported.

In recent times, a sustainable agro-food supply chain network design problem was addressed by Allaoui et al. (2018) through an integrated two-stage hybrid approach. Mohammed and Wang (2017a) simultaneously minimized the transportation cost, required transportation vehicles and delivery time in the meat supply chain. The same authors extended their research with consideration of environmental impact and distribution time (Mohammed and Wang 2017b). They suggested a few extensions of their study by integrating the multi-period, multi-echelon and multi-objective metaheuristic algorithms. Kaur and Singh (2017) proposed a joint sustainable procurement and logistics model considering the emission generated during ordering, holding and logistics. The sustainability in closed-loop supply chain problems can be seen in Banasik et al. (2017), Hasani et al. (2012) and Nurjanni et al. (2017) studies.

Some researchers considered the sustainability in various forms while examining the several FSC problems like two-layer supply chain network design (Validi et al. 2014a, 2015), location-routing (Validi et al. 2018; Govindan et al. 2014), fresh food distribution (Bortolini et al. 2018) and beef/meat logistics network (Soysal et al. 2014, Golini et al. 2017). Majority of these studies have not simultaneously explored various practical features of FSC problems related to multi-period, multiple sourcing, multi-modal transportation and capacitated warehouses. The heterogeneous capacitated vehicles and their limited availability, CO_2 emission produced due to different reasons and vehicle capacity constraints are also not concurrently appeared in these studies. The food quality and sustainability indicators were integrated into discrete event simulation models for the analysis of an integrated approach in the FSC (Van Der Vorst et al. 2009). The metaheuristic approach was suggested for resilient FSC design problem (Bottani et al. 2019). Furthermore, a decision support system was recommended for sales forecasting and order planning operations of fresh FSC (Dellino et al. 2017). The remaining shelf-life of the perishable food was predicted by means of data collected through the sensor network (Li and Wang 2017). A carbon trading mechanism in fresh FSC was introduced by Wang et al.

(2018). The overview of key relevant papers delineating the main features of the model, components of two objective function, decisions taken and the solution methods used are mentioned in Table A.1 in appendix A.

It can be noticed from Table A.1 that most of the authors modelled the problem in the form of MILP or MIP considering the multi-echelon scenario. However, multiple time periods and transportation modes were considered in limited studies. In total cost objective, facility location cost and variable transportation cost were largely taken into account by several researchers. Fixed transportation, inventory and handling costs appeared in a fewer number of articles. Almost all authors mentioned in Table A.1 incorporated the transportation CO_2 emission and few researchers included the CO_2 emission generated due to facility establishment, inventory holding and handling activities. Determination of location and product flows were mostly addressed decisions in literature. The heterogeneous fleet utilized and inventory level were observed in a limited number of research works. Few scholars contributed to food distribution network design regardless of its huge significance (Meneghetti and Monti 2015). The SFSC is considered very contextual because of the variability of food system in various countries (Zhu et al. 2018, Maiyar and Thakkar et al. 2017). There are several factors behind this variability like supply chain actors, different procurement periods, transportation and storage systems and geographically widespread producing and consuming provinces. The involvement of heterogeneous actors and their complex collaborations make the grain supply chain system more complex and dynamic (Swaminathan et al. 1998; Simonson, 2009). Indian food grain distribution system is the world's largest distribution system of its kind and different as well as unique as compared with other developing nations (Balani et al. 2013). Furthermore, managing this system becomes more intricate and difficult as compared to developed economies due to its chaotic nature and a large number of intermediaries (Sachan et al., 2005).

3. Problem statement

The shortfall in storage capacity with FCI can be observed from the statistical data mentioned in subsection 1.3. The policymakers in India are establishing the capacitated warehouses in several geographically dispersed surplus and deficit states to bridge the storage capacity gap. The warehouse establishment decision comes under the strategic category and requires a large amount of initial investment for an establishment based on its capacity levels. In order to curb the CO_2 emission generated due to the travelling of larger distances, more number of warehouses will be required, i.e. large investment and vice-versa. In addition to this, the trade-off occurs between the transportation cost and transportation CO_2 emission due to the fixed hiring cost and emission produced by heterogeneous capacitated vehicles. It means that lower emission from transportation comes at a higher cost. Thus, we have developed a bi-objective mathematical model which seeks to minimize the cost and emission simultaneously. The main goal here is to decide on the locations and on the movement and storage planning in a multi-period environment. The following decision variables are considered (1) location of central, state and district level warehouses (2) optimal quantity of food grain to be moved from procurement centres to fair price shops, (3) inventory available in the central, state and district level warehouses at the end of period, and (4) optimal number of heterogeneous capacitated vehicles used for food grain transportation.

4. Problem formulation

Several assumptions are considered in the formulation of the problem.

- The procurement, demand and storage capacity of central, state and district level warehouses are known and deterministic.
- Potential locations of central, state and district level warehouses are known and fixed.
- The quantity of food grain procured is sufficient to meet the demand of fair price shops.

- Each fair price shops demand should be satisfied during the given time period. Shortages and backlogs are not permitted.
- Three heterogeneous capacitated vehicles with limited availability at each echelon in each time period are available.
- Each vehicle carries Full Truck Load (FTL) transport.

Notations

Indices	Description
p	Index for procurement centres, $p = 1, 2, ..., P$
q	Index for potential central warehouses in surplus states, $q = 1, 2, ..., Q$
r	Index for potential state warehouses in deficit states, $r = 1, 2, ..., R$
s	Index for potential district level warehouses, $s = 1, 2, ..., S$
f	Index for fair price shops, $f = 1, 2, ..., F$
k	Index for truck types available at procurement centres and state warehouse, $k = 1, 2, ..., K$
l	Index for rake types available at central warehouse in surplus state $l = 1, 2, ..., L$
m	Index for truck types available at district level warehouse, $m = 1, 2, ..., M$
t	Index for time period, $t = 1, 2, ..., T$

Parameters	Description
fc_q	Fixed cost of establishing a central warehouse q
fc_r	Fixed cost of establishing a state warehouse r

fc_s	Fixed cost of establishing a district level warehouse s
e_k	Fixed cost of hiring a truck of type k for transportation
e_l	Fixed cost of hiring a rake of type l for transportation
e_m	Fixed cost of hiring a truck of type m for transportation
v	Unit variable transportation cost per km by road mode
u	Unit variable transportation cost per km by rail mode
ic_q	Unit inventory carrying cost per period in central warehouse q
ic_r	Unit inventory carrying cost per period in state warehouse r
ic_s	Unit inventory carrying cost per period in district level warehouse s
hc_q	Unit variable cost for handling one ton of food grain in the central warehouse q
hc_r	Unit variable cost for handling one ton of food grain in state warehouse r
hc_s	Unit variable cost for handling one ton of food grain in the district level warehouse s
g_{pq}	Distance between procurement centre p to central warehouse q
g_{qr}	Distance between central warehouse q *to* state warehouse r
g_{rs}	Distance between state warehouse r to district level warehouse s
g_{sf}	Distance between district level warehouse s to fair price shop f
a_p^t	Amount of grain stock available at procurement centre p during time period t

b_q	Maximum storage capacity of the central warehouse q
b_r	Maximum storage capacity of the state warehouse r
b_s	Maximum storage capacity of the district level warehouse s
d_f^t	Demand of fair price shop f during time period t
α_{kp}^t	Total number of k type of trucks available at procurement centre p in time period t
α_{kr}^t	Total number of k type of trucks available at state warehouse r in time period t
α_{lq}^t	Total number of l type of rakes available at central warehouse q in time period t
α_{ms}^t	Total number of m type of trucks available at district level warehouse s in time period t
Ω_k	Capacity of truck of type k
Ω_l	Capacity of rake of type l
Ω_m	Capacity of truck of type m
ω_q	Amount of CO_2 released while establishing central warehouse q
ω_r	Amount of CO_2 released while establishing state warehouse r
ω_s	Amount of CO_2 released while establishing district level warehouse s

ω^{k}_{pq} Amount of CO_2 released per unit distance for each k type of truck travelling from procurement centre p to central warehouse q

ω^{l}_{qr} Amount of CO_2 released per unit distance for each l type of rake travelling from central warehouse q to state warehouse r

ω^{k}_{rs} Amount of CO_2 released per unit distance for each k type of truck travelling from state warehouse r to district level warehouse s

ω^{m}_{sf} Amount of CO_2 released per unit distance for each m type of truck travelling from district level warehouse s to fair price shop f

δ_q Amount of CO_2 released while handling one ton of food grain in central warehouse q

δ_r Amount of CO_2 released while handling one ton of food grain in state warehouse r

δ_s Amount of CO_2 released while handling one ton of food grain in district level warehouse s

ρ_q Amount of CO_2 released while holding one ton of food grain in central warehouse q

ρ_r Amount of CO_2 released while holding one ton of food grain in state warehouse r

ρ_s Amount of CO_2 released while holding one ton of food grain in district level warehouse s

W	A sufficiently big number

Decision variables	**Description**
Binary variables	
X_q	Equals to 1 if the central warehouse is established at location q and 0 otherwise
Y_r	Equals to 1 if the state warehouse is established at location r and 0 otherwise
Z_s	Equals to 1 if the district level warehouse is established at location s and 0 otherwise
Continuous variables	
E_{pq}^t	The amount of food grain dispatched by procurement centre p to central warehouse q in period t
G_{qr}^t	The amount of food grain dispatched by central warehouse q to state warehouse r in period t
U_{rs}^t	The amount of food grain dispatched by state warehouse r to district level warehouse s in period t
V_{sf}^t	The amount of food grain dispatched by district level warehouse s to fair price shop f in period t
I_q^t	The amount of food grain available at central warehouse q at the end of period t
J_r^t	The amount of food grain available at state warehouse r at the end of period t

B_s^t The amount of food grain available at district level warehouse s at the end of period t

Integer Variables

N_{pq}^{kt} The number of k type of trucks dispatched from procurement centre p to central warehouse q in period t

N_{qr}^{lt} The number of l type of rakes dispatched from central warehouse q to state warehouse r in period t

N_{rs}^{kt} The number of k type of trucks dispatched from state warehouse r to district level warehouse s in period t

N_{sf}^{mt} The number of m type of trucks dispatched from district level warehouse s to fair price shop f in period t

Objective functions:

Objective 1 = Minimization of Total Cost (TC)

Min Obj1 (TC) = Fixed cost of facility location + Transportation cost (fixed and variable cost) + Inventory cost + Handling cost (1)

Fixed cost of Facility location = $\sum_{q\in Q} fc_q X_q + \sum_{r\in R} fc_r Y_r + \sum_{s\in S} fc_s Z_s$ (1.1)

Fixed transportation cost =

$$\sum_{t\in T}\sum_{k\in K}\sum_{p\in P}\sum_{q\in Q} e_k N_{pq}^{kt} + \sum_{t\in T}\sum_{l\in L}\sum_{q\in Q}\sum_{r\in R} e_l N_{qr}^{lt} + \sum_{t\in T}\sum_{k\in K}\sum_{r\in R}\sum_{s\in S} e_k N_{rs}^{kt} + \sum_{t\in T}\sum_{m\in M}\sum_{s\in S}\sum_{f\in F} e_m N_{sf}^{mt} \quad (1.2)$$

Variable transportation cost =

$$\sum_{t\in T}\sum_{p\in P}\sum_{q\in Q} v\ g_{pq}E_{pq}^{t} + \sum_{t\in T}\sum_{q\in Q}\sum_{r\in R} u\ g_{qr}G_{qr}^{t} + \sum_{t\in T}\sum_{r\in R}\sum_{s\in S} v\ g_{rs}U_{rs}^{t} + \sum_{t\in T}\sum_{s\in S}\sum_{f\in F} v\ g_{sf}V_{sf}^{t} \tag{1.3}$$

Inventory cost = $$\sum_{t\in T}\sum_{q\in Q} I_q^t\ ic_q + \sum_{t\in T}\sum_{r\in R} J_r^t\ ic_r + \sum_{t\in T}\sum_{s\in S} B_s^t\ ic_s \tag{1.4}$$

Handling cost =

$$\sum_{t\in T}\left[\sum_{p\in P}\sum_{q\in Q} E_{pq}^{t} + \sum_{q\in Q}\sum_{r\in R} G_{qr}^{t}\right] hc_q + \sum_{t\in T}\left[\sum_{q\in Q}\sum_{r\in R} G_{qr}^{t} + \sum_{r\in R}\sum_{s\in S} U_{rs}^{t}\right] hc_r + \sum_{t\in T}\left[\sum_{r\in R}\sum_{s\in S} U_{rs}^{t} + \sum_{s\in S}\sum_{f\in F} V_{sf}^{t}\right] hc_s \tag{1.5}$$

The calculation of emissions from various sources is the crucial stage in the model formulation. The emission factor based on the total storage capacity of the warehouses is taken into consideration while determining the emission generated because of facility establishment. We have followed the approach of fixed transportation emission per vehicle described in Paksoy et al., (2011) and Mohammed and Wang (2017b) for calculating the transportation emission. The fixed emission factor per unit stocked and handled is considered for calculating the inventory and handling related emissions (Kaur and Singh 2017; Oglethorpe, 2010).

Objective 2 = Minimization of Total Emission of CO_2 (TE)

Min Obj2 (TE) = Emission due to facility establishment + Emission due to transportation

+ Emission due to inventory holding + Emission due to handling (2)

Emission due to facility establishment (EF) = $$\sum_{q\in Q}\omega_q X_q + \sum_{r\in R}\omega_r Y_r + \sum_{s\in S}\omega_s Z_s \tag{2.1}$$

Emission due to transportation (ET) =

$$\sum_{t\in T}\sum_{k\in K}\sum_{p\in P}\sum_{q\in Q}\omega_{pq}^{k} g_{pq} N_{pq}^{kt} + \sum_{t\in T}\sum_{l\in L}\sum_{q\in Q}\sum_{r\in R}\omega_{qr}^{l} g_{qr} N_{qr}^{lt} + \sum_{t\in T}\sum_{k\in K}\sum_{r\in R}\sum_{s\in S}\omega_{rs}^{k} g_{rs} N_{rs}^{kt} + \sum_{t\in T}\sum_{m\in M}\sum_{s\in S}\sum_{f\in F}\omega_{sf}^{m} g_{sf} N_{sf}^{mt} \tag{2.2}$$

Emission due to inventory holding (EI) =

$$\sum_{t\in T}\sum_{q\in Q}\rho_q I_q^t + \sum_{t\in T}\sum_{r\in R}\rho_r J_r^t + \sum_{t\in T}\sum_{s\in S}\rho_s B_s^t \tag{2.3}$$

Emission due to handling (EH) =

$$\sum_{t\in T}\left[\sum_{p\in P}\sum_{q\in Q}E_{pq}^t + \sum_{q\in Q}\sum_{r\in R}G_{qr}^t\right]\delta_q + \sum_{t\in T}\left[\sum_{q\in Q}\sum_{r\in R}G_{qr}^t + \sum_{r\in R}\sum_{s\in S}U_{rs}^t\right]\delta_r + \sum_{t\in T}\left[\sum_{r\in R}\sum_{s\in S}U_{rs}^t + \sum_{s\in S}\sum_{f\in F}V_{sf}^t\right]\delta_s$$

(2.4)

Subject to constraints

The total amount of food grain shipped from the procurement centre to all central warehouses should be less than or equal to the maximum quantity available at a particular procurement centre in a given time period.

$$\sum_{q\in Q}E_{pq}^t \le A_p^t \qquad \forall p,\ \forall t \tag{3}$$

A procurement centre has to transfer the food grain quantity to the established central warehouse only.

$$E_{pq}^t \le WX_q \qquad \forall p,\ \forall q, \forall t \tag{4}$$

The total amount of food grain distributed from central warehouse to all state warehouses is restricted by the maximum available inventory at the respective central warehouse in a given period *t*.

$$\sum_{r\in R}G_{qr}^t \le I_q^t \qquad \forall q,\ \forall t \tag{5}$$

Food grain from the central warehouse is transferred to the state warehouse only if both central and state warehouses are established

$$G_{qr}^{t} \leq WX_{q}Y_{r} \qquad \forall q,\ \forall r,\ \forall t \tag{6}$$

Similarly, the supply restrictions of state warehouse and district level warehouse are represented by constraint (7) and (8) respectively.

$$\sum_{s \in S} U_{rs}^{t} \leq J_{r}^{t} \qquad \forall r,\ \forall t \tag{7}$$

$$\sum_{f \in F} V_{sf}^{t} \leq B_{s}^{t} \qquad \forall s,\ \forall t \tag{8}$$

Food grain from state warehouse is dispatched to district level warehouse only if both state and district level warehouses are constructed.

$$U_{rs}^{t} \leq WY_{r}Z_{s} \qquad \forall r,\ \forall s,\ \forall t \tag{9}$$

Correspondingly, district level warehouse distributes the food grain to fair price shops only if the district level warehouse is established.

$$V_{sf}^{t} \leq WZ_{s} \qquad \forall s,\ \forall f,\ \forall t \tag{10}$$

Total amount of food grain shipped from all district level warehouses should be equal to the demand of fair price shop.

$$\sum_{s \in S} V_{sf}^{t} = d_{f}^{t} \qquad \forall f,\ \forall t \tag{11}$$

The inventory at central warehouse should be lower or equal to the maximum inventory holding capacity of the central warehouse at any time.

$$I_{q}^{(t-1)} + \sum_{p \in P} E_{pq}^{t} \leq b_{q}^{t} \qquad \forall q,\ \forall t \tag{12}$$

Similarly, the capacity constraints of state warehouse and district level warehouse are defined by the constraint (13) and (14) respectively.

$$J_r^{(t-1)} + \sum_{q \in Q} G_{qr}^t \le b_r^t \qquad \forall r,\ \forall t \tag{13}$$

$$B_s^{(t-1)} + \sum_{r \in R} U_{rs}^t \le b_s^t \qquad \forall s,\ \forall t \tag{14}$$

Inventory flow balance equations for central warehouses, state warehouses and district level warehouses are illustrated by Constraints (15), (16) and (17) respectively.

$$I_q^{(t-1)} + \sum_{p \in P} E_{pq}^t - \sum_{r \in R} G_{qr}^t = I_q^t \qquad \forall q,\ \forall t \tag{15}$$

$$J_r^{(t-1)} + \sum_{q \in Q} G_{qr}^t - \sum_{s \in S} U_{rs}^t = J_r^t \qquad \forall r,\ \forall t \tag{16}$$

$$B_s^{(t-1)} + \sum_{r \in R} U_{rs}^t - \sum_{f \in F} V_{sf}^t = B_s^t \qquad \forall s,\ \forall t \tag{17}$$

Total amount of food grain quantity dispatched from procurement centre to central warehouse has to be lower or equal to the total capacity of trucks shipped between the same echelons.

$$E_{pq}^t \le \sum_{k \in K} N_{pq}^{kt} \Omega_k \qquad \forall p,\ \forall q,\ \forall t \tag{18}$$

Correspondingly, the rake capacity constraint between a central and state warehouse, truck capacity constraint between state and district level warehouse, and truck capacity constraint between district level warehouse and fair price shop are specified by constraint (19), (20) and (21) respectively.

$$G_{qr}^t \le \sum_{l \in L} N_{qr}^{lt} \Omega_l \qquad \forall q,\ \forall r,\ \forall t \tag{19}$$

$$U_{rs}^t \le \sum_{k \in K} N_{rs}^{kt} \Omega_k \qquad \forall r,\ \forall s,\ \forall t \tag{20}$$

$$V_{sf}^{t} \leq \sum_{m \in M} N_{sf}^{mt} \Omega_m \qquad \forall s,\ \forall f,\ \forall t \tag{21}$$

The number of each type of trucks utilized from the procurement centre to central warehouse should be within the maximum trucks available at respective procurement centre at a given time period.

$$\sum_{q \in Q} N_{pq}^{kt} \leq \alpha_{kp}^{t} \qquad \forall p,\ \forall k,\ \forall t \tag{22}$$

Likewise, the restrictions on a number of rakes used between central and state warehouse, the number of trucks shipped from state to district level warehouse, and the number of trucks moved from district level warehouse to fair price shops are described using Constraint (23), (24) and (25) respectively.

$$\sum_{r \in R} N_{qr}^{lt} \leq \alpha_{lq}^{t} \qquad \forall q,\ \forall l,\ \forall t \tag{23}$$

$$\sum_{s \in S} N_{rs}^{kt} \leq \alpha_{kr}^{t} \qquad \forall r,\ \forall k,\ \forall t \tag{24}$$

$$\sum_{f \in F} N_{sf}^{mt} \leq \alpha_{ms}^{t} \qquad \forall s,\ \forall m,\ \forall t \tag{25}$$

Binary decision variables which indicate the establishment of central, state and district level warehouses.

$$X_q, Y_r, Z_s \in \{0,1\} \qquad \forall q,\ \forall r,\ \forall s \tag{26}$$

The total amount of food grain quantity dispatched from a procurement centre to a central warehouse, a central warehouse to state warehouse, a state warehouse to a district level warehouse and a district level warehouse to fair price shop should be higher or equal to zero. Also, the inventory available at central, state, and district level warehouse should be higher or equal to zero.

$$E_{pq}^{t}, G_{qr}^{t}, U_{rs}^{t}, V_{sf}^{t}, I_{q}^{t}, J_{r}^{t}, B_{s}^{t} \geq 0 \quad \forall p, \forall q, \forall r, \forall s, \forall f, \forall t \tag{27}$$

Total number of each type of vehicle travelled from a procurement centre to a central warehouse, a central warehouse to state warehouse, a state warehouse to a district level warehouse and a district level warehouse to fair price shops should be an integer.

$$N_{pq}^{kt}, N_{qr}^{lt}, N_{rs}^{kt}, N_{sf}^{mt} \in \mathbb{Z}^{+} \qquad \forall p, \forall q, \forall r, \forall s, \forall f, \forall k, \forall l, \forall m, \forall t \tag{28}$$

5. Research methodology

The classical multi-objective methods including epsilon constraint, goal programming, and weighted sum methods take substantial computational time for solving the real size problem instances because of a large set of variables and constraints (Kadambala et al. 2017; Maiyar and Thakkar 2017; Yu et al. 2017). Moreover, these techniques generate only one optimal point on the Pareto frontier in a single iteration, which lacks credibility in decision making (Pasandideh et al. 2015; Deb, 2001). In the extant literature, several authors have proved the efficiency and effectiveness of MOPSO and NSGA-II algorithms in dealing with bi-objective and multi-objective problems. Indeed, complex multi-objective problems including series-parallel inventory redundancy allocation problem (Alikar et al. 2017), low-carbon distribution system problem (Validi et al. 2014b), cross-docking scheduling problem (Mohtashami et al. 2015) and inventory control problem (Mousavi et al. 2016; Srivastav and Agrawal 2016) are tackled through MOPSO and NSGA-II algorithms. The MOPSO is used due to its ease of execution, the capability of endowing good convergence and preserving a balance between exploitation and exploration (Chakraborty et al. 2011; De et al. 2017; Govindan et al. 2019). The NSGA-II is well recognized, popular and robust algorithm to solve the multi-objective models (Pasandideh et al. 2015; Musavi and Bozorgi-Amiri 2017). Therefore, these two algorithms are implemented to obtain the Pareto optimal solutions to the problem.

The comprehensive steps of these two algorithms and data collection method are represented in the overall research methodology as shown in Figure B.1 (refer Appendix B). The warehouse location-allocation problem is identified from the storage capacity gap associated with the FCI. The critical review of the SFSC problems is carried out to analyse different model characteristics and find out the research gap. Next, the bi-objective mathematical model that seeks to minimize cost and carbon emission is formulated to support the decision-making process of policymakers. The data pertaining to model parameters is gleaned from several reliable sources. The data related to the fixed cost of warehouse locations and its capacity, inventory and operational cost is obtained from the High-level committee report (2015). The data related to supply, demand, potential locations of warehouses, transportation cost, availability of vehicles and its capacity are collected from field visits. The approach used by Nurjanni et al. (2017) and Mohammed and Wang (2017b) is followed while hypothetically simulating the data related to the amount of CO_2 released. The distances between the two locations are determined from the google maps. Table B.1 (Appendix B) provides a summary of these model parameter values. Further, two Pareto based algorithms are selected to solve the bi-objective mathematical model and carried out the parameter tuning of algorithmic parameters. Finally, proposed algorithms are implemented and results are compared following the relevant literature.

5.1 Multi-objective particle swarm optimization (MOPSO)

A population-based optimization technique called particle swarm optimization (PSO) algorithm was proposed by Eberhart and Kennedy (1995) inspired from the behaviour of bird flocking and fish schooling. The PSO algorithm is mainly used for the optimization of single objective models and provides near-optimal solutions. Inspired by the PSO strategy, Moore and Chapman (1999) developed the MOPSO algorithm for solving multi-objective problems, where the Pareto archive is used to store all non-dominated solutions. PSO based algorithms are simple for implementation, needs less parameter setting and balanced mechanism for local and global explorations (Trelea 2003; Zheng et al. 2003). Relying on the detailed flowchart of MOPSO as given in Figure B.1, the initialization, the fast non-dominated sorting and crowding distance steps of MOPSO are similar to the NSGA-II steps. In order to update the velocity of particles, Eq. (29) and (30) are used as follows.

$$v_{t+1}^{i} = wv_{t}^{i} + C_1 r_1 \left(pbest_{t}^{i} - x_{t}^{i} \right) + C_2 r_2 \left(gbest_{t}^{i} - x_{t}^{i} \right) \tag{29}$$

$$x_{t+1}^{i} = x_{t}^{i} + v_{t+1}^{i} \tag{30}$$

Where v_{t+1}^{i} *and* x_{t+1}^{i} are the updated velocity and position vector of an i*th* particle in a *t+1* iteration, r_1 and r_2 are uniformly distributed random numbers between 0 and 1, C_1 and C_2 represent the acceleration constants, *pbest* and *gbest* illustrates the local best for each individual and global best of the population and *w* is the inertia weight. Similar to the NSGA-II, parents and offspring are combined. The algorithm stops when it satisfies the termination criteria of a maximum number of iterations.

5.2 *Non-Dominated Sorting Genetic algorithm II (NSGA-II)*

Deb et al. (2002) proposed NSGA-II as one of the well-known and efficient Pareto based multi-objective algorithms. Several researchers have proved its effectiveness and quality by tackling complex engineering and combinatorial multi-objective problems through NSGA-II (Govindan et al. 2014; Kadambala et al. 2017; Mohtashami et al. 2015). The problem is solved using the NSGA-II through the implementation of the several key steps mentioned in Figure B.1. The full explanation of the NSGA-II algorithm is provided in Appendix C.

6. Results and discussion

Initially, fifteen problem instances are generated following the collected secondary data for verification and validation of the model. The problem characteristics include the number of procurement centres (PC), central warehouses (CW), state warehouses (SW) and district-level warehouses (DLW), fair price shops (FPS) and time periods (TP). These test problems are classified into three sizes: small, medium and large scale according to Table 1. Moreover, the complexity of the model in terms of a number of decision variables and constraints in each test problem is presented in the same table.

Table 1 Different problem instances and its complexity

Problem size	Problem instance number	PC(P)	CW(Q)	SW(R)	DLW(S)	FPS(F)	TP(T)	Decision variables				Constraints		
								Binary	Continuous	Integer	Total	Equality	Inequality	Total
Small scale	I1	4	2	3	6	8	2	11	182	480	673	529	644	1173
	I2	6	3	5	9	11	2	17	388	1062	1467	1135	1314	2449
	I3	8	4	6	11	13	2	21	572	1590	2183	1679	1906	3585
	I4	10	5	7	12	15	2	25	782	2196	3003	2301	2576	4877
	I5	11	6	8	13	16	2	27	906	2556	3489	2669	2968	5637
Medium scale	I6	12	7	9	14	18	3	30	1665	4725	6420	4899	5386	10285
	I7	15	8	11	18	21	3	37	2463	7056	9556	7267	7873	15140
	I8	18	10	13	21	25	3	44	3456	9972	13472	10223	10946	21169
	I9	20	11	15	25	29	3	51	4608	13365	18024	13656	14483	28139
	I10	22	13	17	28	32	3	58	5811	16911	22780	17239	18174	35413
Large scale	I11	25	15	20	30	35	4	65	9560	27900	35525	28365	29760	58125
	I12	27	18	22	33	38	4	73	11740	34344	46157	34861	36418	71279
	I13	30	20	25	35	40	4	80	13820	40500	54400	41060	42780	83840
	I14	40	25	30	45	55	4	100	22700	66900	89700	67620	69790	137410
	I15	50	30	35	55	70	4	120	33780	99900	133800	100780	103400	204180

Parameter setting of the algorithm is one of the crucial aspects. The solution quality and convergence velocity mostly depend on it (Mousavi et al. 2016; Kadambala et al. 2017). Therefore, several preliminary computational experiments are performed to find out suitable parameters. The tuned algorithm parameters of NSGA-II algorithm are as follows: (1) Population size = 50; (2) crossover probability = 0.9; (3) mutation probability =

0.1 and (4) number of generations = 200. Similarly, we have set the following suitable parameters for MOPSO algorithm. (1) Swarm size = 50; (2) Inertia weight = 0.9; (3) Cognition acceleration parameter = 0.1; (4) Social acceleration parameter =0.95 and (5) number of generations = 200.

The Matlab (R2018a) software is used for computer coding of both algorithms. All computational experiments are run on a computer with Intel Core i5, 2.90 GHz processor with 8 GB RAM. Each problem instance is solved by means of MOPSO and NSGA-II algorithm with calibrated parameters. The obtained solutions of the model in terms of "minimum", "intermediate", and "maximum" values of the first objective (total cost) and the second objective function (total CO_2 emission) along with the computational time for all instances using proposed two algorithms are reported in Tables 2(a) and (b) respectively. The "minimum" and "maximum" portrays the highest and lowest values of a particular objective in the Pareto front. Both the objectives are treated in the same way and given equal importance (weights) while selecting the Pareto optimal solution (intermediate) among the set of non-dominated solutions. The Pareto optimal solution mentioned in Tables 2(a) and (b) is one among the set of Pareto solutions obtained in several runs. It can be observed from these tables that MOPSO algorithm performs better compared to NSGA-II for all considered problem instances. The CPU time taken by the NSGA-II algorithm to solve each problem instance is higher than the MOPSO. These results support the findings of Kadambala et al. (2017), Maghsoudlou et al. (2016) and Srivastav and Agrawal (2016). The cost minimal and emission minimal solution pertaining to the first problem instance is evaluated and reported in Table 3. It can be noticed from this table that if decision makers aspire to optimize the cost over the emission, the best choice has a cost value of 52.89 m and emission value of 338.59 mt. In another case, if policymakers wish to optimize emission over the cost then the values mentioned in the second row of Table 3 will be the best alternative. Finally, if there is no priority among the two objectives, an intermediate (best compromise) solution reported in the last row of Table 3 will be the best option.

Table 2(a) Computational results obtained using MOPSO algorithm

Problem instance	Total cost (millions $)			Total CO_2 emission (mt)			Computational Time (sec)
	min	inter	max	min	inter	max	
I1	52.89	55.24	56.90	338.05	338.37	338.59	13.77
I2	169.42	170.37	172.13	909.32	909.56	909.72	28.37
I3	275.31	276.80	278.18	1610.89	1610.95	1611.07	40.23
I4	448.74	449.71	450.39	2507.52	2507.87	2508.10	54.35
I5	538.08	539.25	540.71	2813.00	2813.05	2813.09	63.18
I6	1072.59	1075.23	1079.32	6184.82	6185.33	6185.75	114.20
I7	1674.47	1680.00	1683.42	8783.45	8784.21	8788.12	172.06
I8	2392.93	2401.22	2404.90	11963.13	11964.56	11965.23	238.19
I9	3134.22	3134.89	3137.02	15422.08	15423.24	15423.95	331.25
I10	3849.36	3849.90	3852.96	20919.80	20920.51	20921.12	416.54
I11	7800.14	7806.14	7810.66	36116.76	36118.40	36121.08	689.67
I12	9768.32	9772.49	9774.73	48422.48	48423.25	48424.01	863.52
I13	10919.80	10927.71	10937.41	62211.27	62214.79	62222.41	961.77
I14	18114.15	18121.74	18131.70	92109.07	92109.59	92109.92	1585.02
I15	26053.81	26060.15	26066.17	132163.45	132167.64	132172.01	2380.36

Table 2(b) Computational results obtained using NSGA-II algorithm

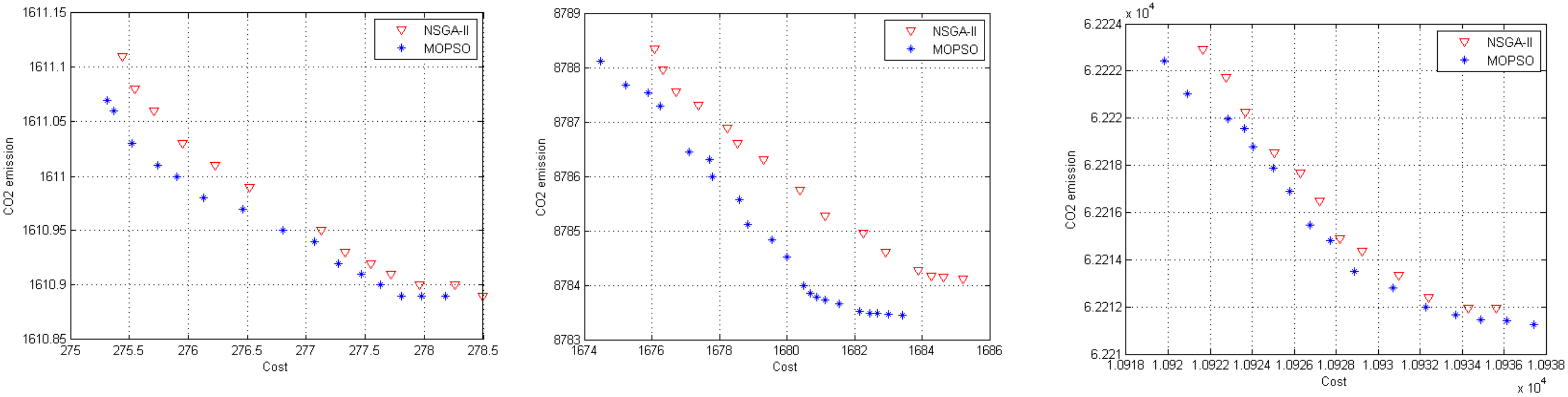
Problem instance	Total cost (millions $)			Total CO_2 emission (mt)			Computational Time (sec)
	min	inter	max	min	inter	max	
I1	53.21	55.46	57.28	338.12	338.45	338.63	17.32
I2	169.66	170.49	172.40	909.26	909.66	909.79	36.75
I3	275.44	277.13	278.50	1610.93	1610.99	1611.13	57.83
I4	449.08	449.84	450.55	2507.65	2507.94	2508.15	68.59
I5	538.24	539.45	540.94	2813.33	2813.57	2813.60	90.24
I6	1073.28	1075.49	1080.22	6184.72	6185.43	6185.87	136.59
I7	1676.08	1680.39	1685.21	8784.11	8785.74	8788.35	198.34
I8	2393.15	2401.46	2405.16	11963.39	11964.63	11965.48	287.78
I9	3134.48	3135.08	3137.26	15422.46	15423.39	15424.26	392.04
I10	3849.53	3850.04	3853.17	20919.86	20920.98	20921.33	475.87
I11	7800.42	7806.34	7810.98	36116.92	36118.48	36121.13	767.38
I12	9768.83	9772.90	9775.86	48422.71	48423.92	48425.29	907.61
I13	10921.66	10928.19	10935.64	62211.94	62214.91	62222.92	1095.94
I14	18119.89	18125.84	18136.28	92109.41	92109.77	92110.60	1657.89
I15	26054.31	26060.37	26067.16	132163.83	132167.76	132172.30	2528.76

Table 3 Payoff matrix for first problem instance

Objective functions	Total cost (m$)	Total CO_2 emission (mt)
Total cost	**52.89**	338.59
Total CO_2 emission	56.90	**338.05**
Best compromise solution	55.24	338.37

One test instance from each problem category is selected to ensure conciseness in discussing the results of the optimization model. Figures 2(a) - (c) portray the Pareto frontier of both optimization techniques for the chosen three problem instances. MOPSO provides suitable Pareto solutions with more number of Pareto points on the efficient frontier compared to

NSGA-II. These Pareto points will be beneficial to the policymakers while designing the SFSC network. According to the policymakers' preferences, they can select any one solution from the set of Pareto optimal solutions. In the literature, Harris et al. (2014); Nurjanni et al. (2017); Soysal et al. (2014); Validi et al. (2014b), Guo et al. (2018) and Wang et al. (2011) discussed the similar type of solution behaviour. The nature of the obtained Pareto frontier is compatible with their results.



(a) (b) (c)

Figure 2. Pareto frontier of (a) third problem (b) seventh problem and (c) thirteenth problem

A brief summary of all the values of decision variables considering finite planning horizon pertaining to each selected problem instance is analyzed and reported in Figures 3(a) and (b). Consolidated quantity of food grain transported between each stage and inventory available in the different warehouses at the end of the periods are represented in Figure 3(a). The carbon emission caused due to transportation activities mainly depends on the vehicles dispatched for transporting food grains between echelons. Hence, Figure 3(b) illustrates the aggregated heterogeneous vehicles dispatched within an overall planning period for food grains movement. The escalation in the quantity shipped between each stage and corresponding vehicles moved against the increment in the problem scale are perceived from these two figures.

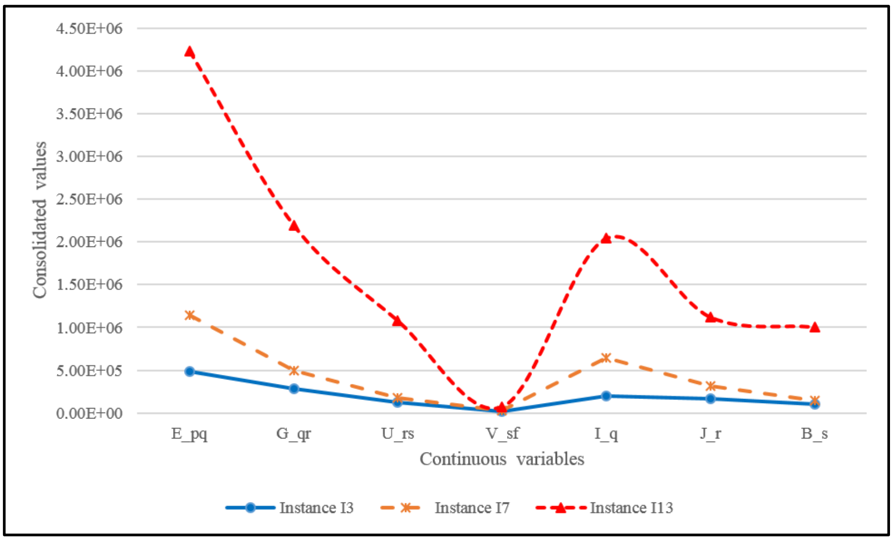


Figure 3 (a) Consolidated grain quantity transferred and inventory level

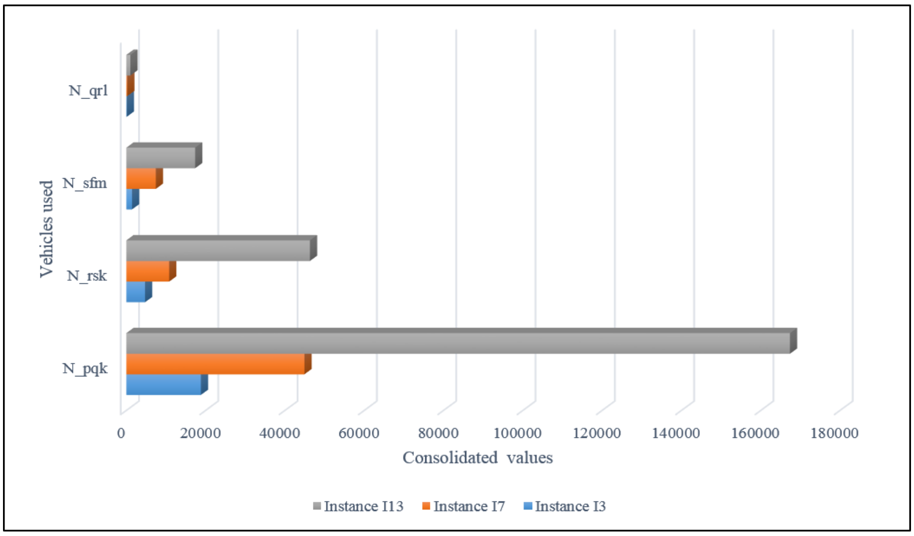


Figure 3 (b) Consolidated number of vehicles utilised

Sensitivity analysis

The sensitivity analysis is conducted on the problem instance three to visualize the influence of the model parameters on two objectives and to obtain more insights for the improvement in the current SFSC. The number of procurement centres (supply) and the number of fair price shops (demand) are two crucial parameters of the model. Therefore, these two parameters are taken into consideration to observe the impact of variation in supply and demand. Figures 4(a) and (b) depict the effect of the deviation of a number of procurement centres from -50% to +50% of its current value on cost and CO_2 emission respectively. The supply network cost is increased (35.67%) and decreased (19.33%) when the number of procurement centres increased and decreased (50%), respectively. Similarly, the increment of 50% in a number of procurement centres decrease the CO_2 emission by 2.04% and decrement of 50% increases the emission by 3.52%. The changes in the values of each component of two objectives can also be viewed from Figures 4(a) and (b). In a similar way, the fluctuations in the numerical values of two objectives along with their elements are reported in Figures 5(a) and (b) after varying the number of fair price shops by +50%, +25%, -25% and -50% from its original value. It is observed from figure 5(a) that total cost increased and decreased when the number of fair price shops increased and decreased. The CO_2 emission is diminished (4.65%) and increased (11.73%) after the 50% increment and reduction in a number of fair price shops. Following these relationships, policymakers should focus on establishing an adequate number of warehouses in surplus and deficit states by maintaining the proper balance between two objectives. Various acronyms used in Figures 4 (a, b) and 5 (a, b) for describing the several components of cost and emission objectives are elaborated as follows. FLC - Facility location cost, TRC - Transportation cost, INC - Inventory cost, HAC - Handling cost and TC - Total cost. EFL – Emission produced during facility establishment, ET – Transportation emission, EI – Emission generated due to the stocking of inventory, EH – Emission generated due to handling activities and TE – Total emission.

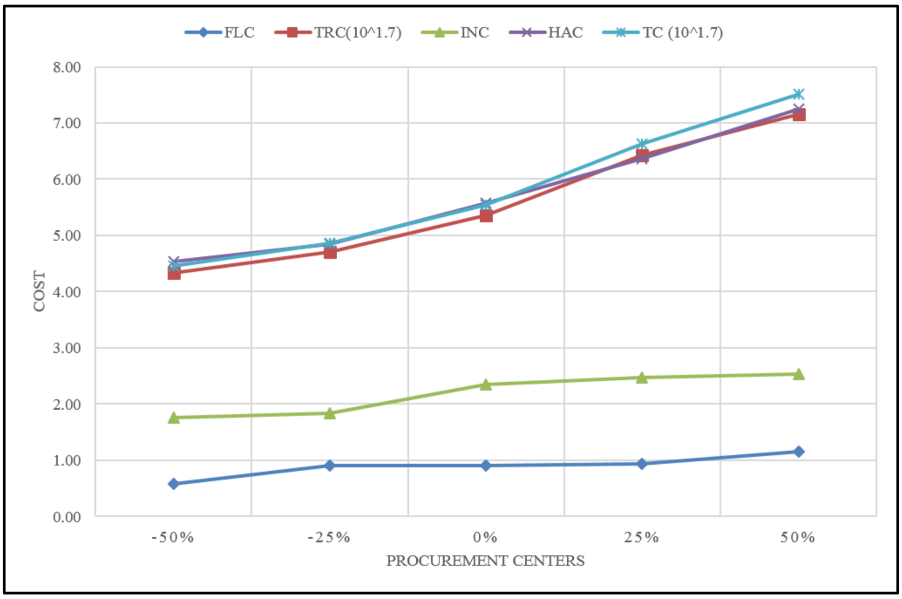


Figure 4(a). The impact of variations in supply (procurement centres) on cost

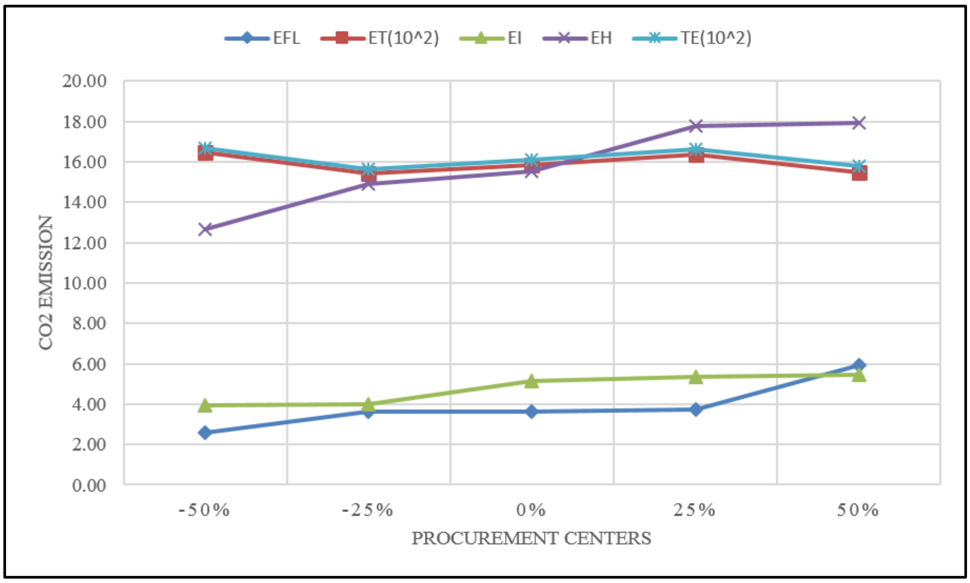


Figure 4(b). The impact of variations in supply (procurement centres) on CO_2 emission

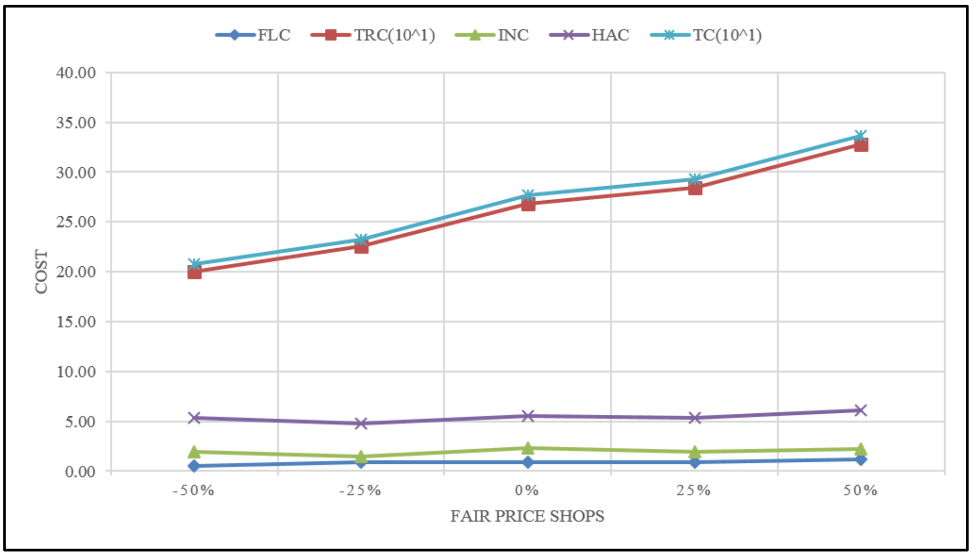


Figure 5(a). The impact of variations in demand (fair price shops) on cost

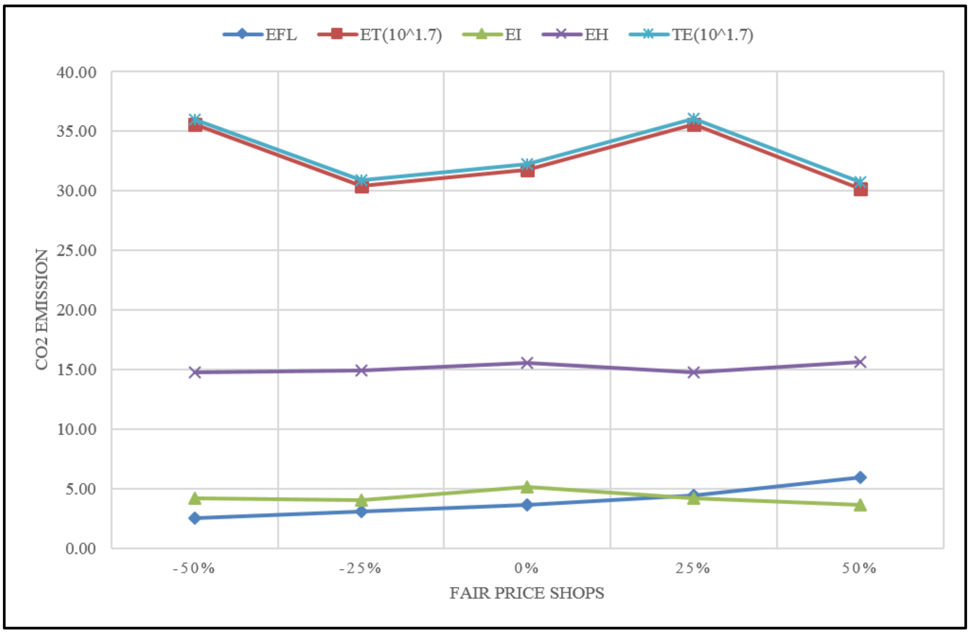


Figure 5(b). The impact of variations in demand (fair price shops) on CO_2 emission

7. Conclusion and future scope

This study aimed to explore the sustainability in FSC domain by developing a decision support model integrating the economic and environmental dimensions. The storage capacity gap, increment of food grain stock, colossal post-harvest losses and degrading environment are some of the key motivations behind this study. The development of a bi-objective mathematical model by integrating the several problem peculiarities to support the strategic and tactical decision-making process of policymakers is the main contribution of our work. The formulated mathematical model is competent enough to demonstrate the trade-offs between cost and CO_2 emission. Small, medium and large scale problem instances stimulated from food grain supply chain in India are solved using two Pareto based multi-objective algorithms. The solution obtained through MOPSO algorithm is superior compared with NSGA-II algorithm. Sensitivity analysis results imply that the decision makers should establish a sufficient number of warehouses in each producing and consuming states by maintaining the suitable balance between the two objectives. Some of the crucial managerial insights and theoretical implications which can improve the efficacy and effectiveness of the present food grain supply chain pertaining to the results of the study are delineated here.

7.1 Theoretical implications

This research study delivers the theoretical contributions to the recent topic of sustainability in the FSC. Existing research work of Banasik et al. (2019), Mohammed and Wang (2017b), Seuring (2013), Maiyar and Thakkar (2017), Brandenburg et al. (2014) and Wang et al. (2019) argued the growing attention of the environmental impact of FSC activities along with economic influence. New mathematical models are necessary to improve the FSC in developing nations by integrating sustainability, multiple time periods, integration of procurement, transportation and storage decisions (Esteso et al. 2018, Zhu et al. 2018). They also emphasized the integration of economic and environmental aspects and their conflicting nature and multi-objective modelling in SFSC domain. Following these arguments, a novel decision support model which aims to minimize the cost and emission is presented to design the SFSC network.

Furthermore, past studies mainly focused on multi-echelon supply chain network with facility location, variable transportation costs and transportation emission (Banasik et al. 2017, Mohammed and Wang 2017a, 2017b, Validi et al. 2014a, 2018). Few scholars evaluated the location and transportation related decisions in their works (Musavi and Bozorgi-Amiri 2017, Govindan et al. 2014). Therefore, several practical characteristics like multiple time periods and transportation modes, heterogeneous capacitated vehicles and their limited availability, multiple sourcing and distribution, geographically dispersed producing and consuming states, capacitated warehouses and vehicle capacity restrictions are simultaneously integrated into the developed model. The transportation emissions affected by vehicle types, load of vehicles and travelled distances, emission caused due to facility establishment, holding and handling operations are also considered in the model. A comparative analysis of two meta-heuristic algorithms on the food grain supply chain problem in developing economy is also distinctive which bridges the research gap of algorithms/heuristics applications in SFSC domain (Esteso et al. 2018, Zhu et al. 2018, Validi et al. 2015, Mohammed and Wang 2017b, Allaoui et al. 2018). The influence of supply and demand uncertainty is captured through the sensitivity analysis which overlooked in the Validi et al. (2014b) and Maiyar and Thakkar et al. (2017) studies.

7.2 Managerial implications

The different actors involved in the FSC including farmers, state government agencies of surplus and deficit states, private transporters, FCI and railways get several insights from this research. Due to the increment of central food grain stock and gloomy capacity addition in the last decade, policymakers should bridge the storage capacity gap by establishing adequate warehouses across the country. The proposed decision support model can be used for the feasibility analysis of the various potential locations that help to evade the loss of huge capital investment. The establishment of central warehouses in surplus states will be helpful for quick transfer of food grain stock from procurement centres to central warehouses. This will results in the increment of procurement from farmers and they get the benefit of MSP which improves their economic and welfare growth. Similarly, the construction of state and district level warehouses will be useful for the effective distribution of food grains in deficit states and reducing the malnutrition by satisfying the demand of the people. Due to the construction of new warehouses, farmers and other actors travel the fewer distances to reach the nearby warehouses. This leads to a reduction in transportation cost and associated emission between different stages. The less emission will be instrumental to decrease the carbon tax of transportation activities. The emission generated by trucks is higher than the rail, hence decision makers can focus on utilization of rail rather than truck wherever possible. Therefore, transportation activities need a particular interest while establishing warehouses. The storage losses of food grain stock by keeping it in open storage will be significantly lowered due to the establishment of new warehouses. Overall, the majority of the problems related to storage, transportation, post-harvest losses, a huge amount of hiring and carry overcharges can be resolved after the availability of sufficient storage capacity. Also, policymakers can curb the emission produced due to central food grain stock and associated handling activities by maintaining the optimal inventory in different warehouses.

The Pareto optimal solutions obtained are helpful for the policymakers to maintain the proper trade-off between cost and carbon dioxide emission. The movement and storage activity plan in a definite planning horizon with the consideration of carbon emission can be prepared using the results of this model. Policymakers can make the various strategies and plans based on the heterogeneous capacitated vehicles movement to minimize the transportation cost and associated emission. The issues related to vehicles requirement and their scheduling along with shortages can be resolved through the time-dependent movement plan of vehicles. The storage activity plan will be useful for the optimal utilization of resources.

Limitations and future scope

Similar to the other studies, the current study has a few limitations which open the doors for future research. The stochastic or fuzzy multi-objective model can be formulated in the near future to capture the uncertainty in procurement and demand parameters. The present model integrated the economic and environmental dimension of sustainability. We have not explored the social dimension due to the difficulty in quantifying the social factors (Esteso et al. 2018, Zhu et al. 2018). Also, water footprint needs to be incorporated in future decision support models to evaluate the impact of FSC activities on it. The current model needs the set of potential location of different warehouses for the establishment. However, in few instances, policymakers can ask for support to determine potential locations of warehouses. The inclusion of the minimization of lead time objective is another possible extension of the present model. The current study considered single food grain and future research can look into the multi-food grain scenario. The quantification of the post-harvest losses is another avenue for research. The proposed two metaheuristic algorithms can be applied to other problems like location-routing, hub location and scheduling, and vehicle routing problems in crop based and animal based agro food supply chain to evaluate its effectiveness.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix A

Table A.1 Comparative study of relevant literature with present work

	Model features				Objective functions									Decisions				Solution method
					Economic objective components					Environmental objective components								
										CO_2 emission generated due to								
Study	Multi-period	Multi-modal	Multi-echelon	Approach	FLC	FTC	VTC	IC	HC	FE	TR	IH	HA	L	HFU	PF	IL	
Allaoui et al. (2018)	✓	✓	✓	MILP	✓	×	✓	×	×	✓	✓	×	×	✓	×	✓	×	Epsilon constraint
Banasik et al. (2017)	✓	×	✓	MILP	✓	×	✓	×	✓	×	✓	×	×	✓	×	✓	×	Epsilon constraint
Govindan et al. (2014)	✓	×	✓	MIP	✓	✓	✓	×	✓	✓	✓	×	✓	✓	×	✓	×	MOPSO and NSGA-II
Mohammed and Wang (2017a)	×	×	✓	MILP	×	×	✓	×	×	×	×	×	×	✓	✓	✓	×	LP metrics, Epsilon constraint and Tchebycheff methods
Mohammed and Wang (2017b)	×	×	✓	MILP	×	×	✓	×	✓	✓	✓	×	×	✓	×	✓	×	LP metrics, Epsilon constraint and goal programming
Musavi and Bozorgi-Amiri (2017)	×	×	✓	MILP	×	×	✓	×	×	×	✓	×	×	✓	×	✓	×	NSGA-II and Epsilon constraint
Nurjanni et al. (2017)	×	✓	✓	MILP	✓	×	✓	×	✓	×	✓	×	✓	✓	×	✓	×	Weighted sum, Tchebycheff and augmented Techeby.
Soysal et al. (2014)	✓	✓	✓	MILP	×	✓	✓	✓	×	×	✓	×	×	×	✓	✓	✓	Epsilon constraint
Validi et al. (2014a)	×	×	✓	MIP	✓	✓	✓	×	×	×	✓	×	×	✓	✓	✓	×	NSGA-II, MOGA-II and Hybrid
Validi et al. (2018)	×	×	✓	MIP	✓	×	✓	×	×	×	✓	×	×	✓	×	×	×	MOGA-II
Our study	✓	✓	✓	**MINLP**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	**MOPSO and NSGA-II**

Approach*: MILP= Mixed integer linear programming; MIP= Mixed integer programming; MINLP = Mixed integer non-linear programming;*

Economic objective components*: FLC= Facility location cost; FTC= Fixed transportation cost; VTC= variable transportation cost; IC= Inventory cost; HC= Handling cost*

Environmental objective components*: CO_2 emission generated due to FE= Facility establishment; TR= Transportation; IH= Inventory holding; HA= Handling activities*

Decisions
Strategic: L= Location, HFU = Heterogeneous fleet utilized; PF= Product flows; IL= Inventory level

Appendix B

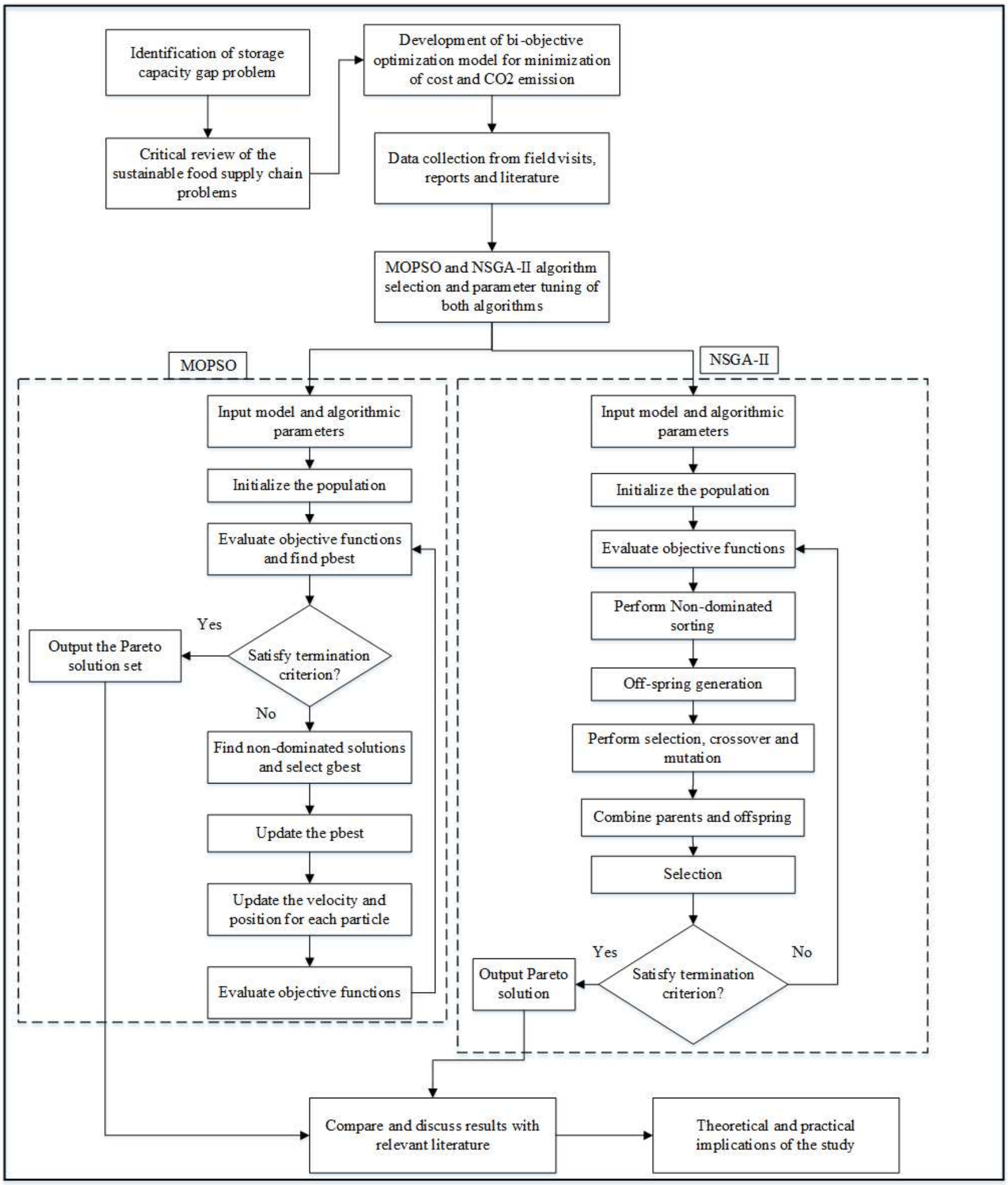

Figure B.1 Research methodology

Table B.1 Summary of model parameter values

Parameters	Range of values	Parameters	Range of values
fc_q	USD 400000-500000	d_f^t	200-700 MT
fc_r	USD 100000-200000	α_{kp}^t	500-1000
fc_s	USD 20000-80000	α_{kr}^t	300-500
e_k	USD 50-30	α_{lq}^t	5-30
e_l	USD 300-150	α_{ms}^t	200-400
e_m	USD 20-10	Ω_k	20-30 MT
v	USD 0.69	Ω_l	1500-3000 MT
u	USD 0.52	Ω_m	8-12 MT
ic_q, ic_r, ic_s	USD 5	ω_q	1386-2310 Kg
hc_q, hc_r, hc_s	USD 4.23	ω_r	462-924 kg
g_{pq}	15-100 Km	ω_s	115-323 kg
g_{qr}	500-2500 Km	ω_{pq}^k	0.150-0.225 kg
g_{rs}	200-500 Km	ω_{qr}^l	9-20 kg
g_{sf}	10-80 Km	ω_{rs}^k	0.150-0.225
a_p^t	20000-40000 MT	ω_{sf}^m	0.06-0.09 kg
b_q	150000–250000 MT	$\delta_q, \delta_r, \delta_s$	0.0118 kg
b_r	50000–100000 MT	ρ_q, ρ_r, ρ_s	0.01095 kg
b_s	12500–35000 MT		

Appendix C

Non-Dominated Sorting Genetic Algorithm (NSGA-II)

Chromosome structure and initialization

The solution to the problem is encoded in the chromosome in the form of multi-dimensional arrays. The set of decision variables comprising of binary (Eq. 23), continuous (Eq. 24) and integer (Eq. 25) variables are the part of the chromosome. The values of these decision variables are generated randomly, within an upper and a lower limit of decision variables.

Non-Dominated Sorting

In the non-dominated set, a particular solution cannot be dominated by any other solution in that set. Different non-dominated solutions in the form of sets are obtained through non-dominated sorting and these sets are called front in multi-objective case. Initially, a temporary population is generated by combining the parent and offspring populations. We set n_p as the number of solutions that dominate a solution p and S_p as the set of solutions that are dominated by the solution p. The n_p and S_p are determined for each specific solution in the combined set. Now all the solutions with zero n_p value are included in the first set of non-dominated solutions. We traverse through the solutions in S_p for all the population with n_p=0 and go on reducing the domination value until it reaches zero. Then, all these solutions are isolated into 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 subsequent fronts are identified.

Crowding Distance

This parameter is used for estimating the density of the solutions surrounding a specific solution in the population. To find out the crowding distance of a particular solution, an average distance of two neighbouring solutions on either side of that solution along each objective function is determined.

Genetic Operators

In order to produce the offspring from the current population, genetic operators including mutation and crossover are employed in the algorithm. Mutation is used for obtaining diversified solutions and a crossover is used for combining the previous solutions into others. The offspring is generated by means of simulated binary crossover operator and polynomial mutation operator because of real number encoding.

Selection

Selection is performed for evaluating the individuals of the next generation when the offspring population combines with the current population. Crowd comparison operator selects the best set of solutions after solutions sorting and crowding distance assignment procedure. The lowest rank solutions are more preferred, however, if two solutions get the same rank, then the solution is selected based on the highest crowding distance criterion. Finally algorithm stops when it satisfies the terminations criteria of maximum iterations and provides the set of Pareto optimal solutions.