Green food supply chain design considering risk and post-harvest losses: a case study

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Abstract

The global food insecurity, malnourishment and rising world hunger are the major hindrances in accomplishing the zero hunger sustainable development goal by 2030. Due to the continuous increment of wheat production in the past few decades, India received the second rank in the global wheat production after China. However, storage capacity has not been expanded with similar extent. The administrative bodies in India are constructing several capacitated silos in major geographically widespread producing and consuming states to curtail this gap. This paper presents a multi-period single objective mathematical model to support their decision-making process. The model minimizes the silo establishment, transportation, food grain loss, inventory holding, carbon emission, and risk penalty costs. The proposed model is solved using the variant of the particle swarm optimization combined with global, local and near neighbor social structures along with traditional PSO. The solutions obtained through two metaheuristic algorithms are compared with the optimal solutions. The impact of supply, demand and capacity of silos on the model solution is investigated through sensitivity analysis. Finally, some actionable theoretical and managerial implications are discussed after analysing the obtained results.

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1 Introduction and motivation

The global food security is a major policy concern due to the rising worldwide population, climate change and increasing food demand (Ge et al. 2018; Kaur 2019; Maiyar and Thakkar 2019; Nicholson et al. 2011). The third of total arable land on this planet has lost in the past 40 years (Milman 2015) and only 12 percent land across the globe is cultivated (Sheane et al. 2018). Additionally, the post-harvest loss is one of the vital factors which greatly impacts global food security (An and Ouyang 2016; Kiil et al. 2018; Krishnan et al. 2020; Raut et al. 2018). The annual loss of around 1.3 billion tons closely one-third of the total food produced in the world raises the pressure on global food security (Gustavsson et al. 2011). The monetary value of the food loss and waste in the developed and developing nations are nearly USD 680 billion and 310 billion respectively (FAO 2011). Close to 40% of the food gets wasted in the developing countries during postharvest stage whereas the same amount lost at retail and consumer levels in industrialised nations (FAO 2011). These losses also contribute significantly to squandering of resources like land, water, labour, energy and money and unnecessarily produces the greenhouse gas emissions which causes the global warming and climate change (FAO 2011; Göbel et al. 2015). Today, more than 820 million individuals corresponding to one in every nine people on the globe still suffering from the hunger which creates the challenge for achieving the zero hunger sustainable goal by 2030 (FAO 2019).

The post-harvest losses are not curbed in India despite the increment of production of food grains in the past few decades and still, these are approximately 10% (Sharon et al. 2014). The storage loss of nearly 6% contributes a significant proportion of post-harvest losses because of inadequate and outdated storage facilities (Sharon et al. 2014). In India, annually about 12 to 16 million tons of food grain is wasted with an approximate worth of USD 4 billion. This food grain amount is enough to feed approximately 10% of India's population and means that appropriate storage and reduction of storage losses can help to meet the 10% of India's food demand (Alagusundaram 2016). The improper handling and traditional storage practices, poor collaboration among supply chain members, inadequate storage facilities and lack of transportation infrastructure, as well as extremely ineffective supply chain, are the paramount reasons of colossal food grain losses (Sachan et al. 2005; Parwez 2014; Maiyar and Thakkar 2017; Mogale et al. 2017; Chauhan et al. 2019). Transportation activities come under one of the main sources of air pollution which creates detrimental impacts on public health and the environment (Wang et al. 2011; Song et al. 2014). India placed at third position after China and the USA in the worldwide GHG emission ranking (Timperley 2019). In this country, roughly 5 million tons of crops get spoiled because of toxic gases (Ramanathan et al. 2014). Thus, the environmental aspect needs to be considered while tackling food supply chain issues (Mohammed and Wang 2017; Banasik et al. 2017; Yakavenka et al. 2019; Mogale et al. 2019a).

The current research work is allied with food grain supply chain activities in India. The major activities such as procurement, storage, movement, and distribution are depicted in Fig. 1. Initially, procurement of food grains mainly wheat and rice is carried out and then the procured food grain is stored into various central warehouses and base silos located in producing (surplus) states. Next, food grain is transferred to the various deficit (consuming) states because of the discrepancy between the supply and demand (Mogale et al. 2019b; Maiyar and Thakkar 2017). Finally, the deficit states distribute the food grains at the subsidized rates to the beneficiaries (CAG 2013). According to CAG 2013 report, central pool stock of food grain has steadily increased to 67 Million Metric Ton (MMT) in
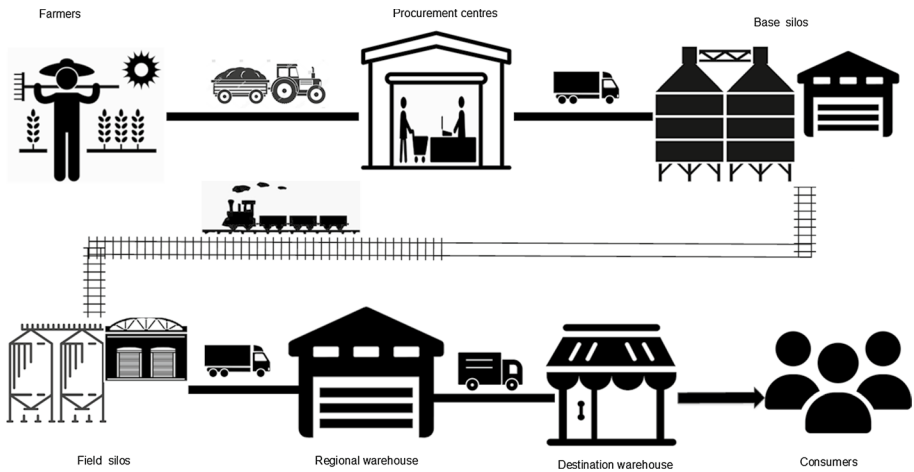
Fig. 1 Schematic representation of food grain supply chain in India (Mogale et al. 2018a)

2012 from 21 MMT in 2007, while the capacity has increased by a merely 0.4 MMT during the same span of time (Mogale et al. 2018a; 2019a). A significant discrepancy between the central pool stock and total storage capacity can be witnessed from the aforementioned statistics, hence, storage capacity must be increased to cope with growing procurement. To fill the gap of storage capacity, policymakers in India commenced the establishment of capacitated silos in the major food grain surplus and deficit states. The silos constructed in producing and consuming states are called as base silo and field silo, respectively (Mogale et al. 2018a).

The rest of the article is structured as follows. Section 2 provides a literature review of related topics. Section 3 delineates the problem and mathematical model. Section 4 explicates details about the implemented algorithms. Section 5 analyses and discusses the several real-life problem instances and their computational results. Finally, Sect. 6 concludes the article with some future scope of the work.

2 Literature search

The problem addressed in this paper comes under the category of the supply chain network design (SCND). A large body of literature in the domain of SCND problems is available. Thus, a review of existing relevant literature focusing on integrated SCND models, post-harvest loss minimization, sustainability, risk management, computational tools, and review articles in the context of the food supply chain are discussed in this section.

2.1 Models for SCND problems

Hosseini-Motlagh et al. (2019), Naderi et al. (2019) and Gholamian and Taghanzadeh (2017) proposed mathematical models for wheat SCND problem in Iran. Further, the realistic case of wheat logistics planning problem concentrating on inventory transportation issues in Iran was solved by Asgari et al. (2013). The bimodal transportation (Etemadnia

et al. 2015) and intermodal transportation (Maiyar and Thakkar 2019) from surplus to defi-cit regions were integrated while dealing with the hub location problem of the food supply chain. Ge et al. (2015) developed the optimization and simulation models for the Cana-dian grain industry to minimize the operational cost of the wheat supply chain. However, food grain losses, risk penalty cost and fleet management are absent in the aforementioned studies. Moreover, mathematical models for the SCND of edible vegetable oils producer (Paksoy et al. 2012), food bank (Orgut et al. 2017), food aid distribution (Rancourt et al. 2015) and fresh produce facilities (Ge et al. 2018) were proposed. Interested readers are recommended to refer the review articles of Soto-Silva et al. (2016), Arabani and Farahani (2012), Farahani et al. (2010), Melo et al. (2009), ReVelle and Eiselt (2005), Akkerman et al. (2010), Zhu et al. (2018) and Eskandarpour et al. (2015) for more information on SCND problems.

2.2 Post-harvest losses and risk management in food supply chains

Nourbakhsh et al. (2016) and An and Ouyang (2016) considered the post-harvest losses while formulating the optimization model for grain supply chain problem. Mishra and Singh (2018) presented the framework for waste minimization in the beef supply chain using twitter data. A location model was introduced for perishable food facilities consid-ering losses from variations in temperature and relative humidity (Orjuela-Castro et al. 2017). A multi-objective mathematical model considering the economic and environmen-tal aspect was formulated by Banasik et al. (2017) to evaluate alternate production options for waste management in the food supply chain. Dora et al. (2019) identified the food loss hotspots in Belgian food processing industry. Sustainability aspect was integrated into the different models of food supply chain using single or multi-objective approaches by several authors in their studies (Allaoui et al. 2018; Validi et al. 2014; Soysal et al. 2014; Govindan et al. 2014; Maiyar and Thakkar 2019; Mogale et al. 2019a; and Validi et al. 2018).

Few researchers investigated the various risks involved in the food supply chains. A mathematical model for routing-location of hazardous materials was developed to opti-mize the cost and risk involved in supply chain (Ardjmand et al. 2016). Further, Diabat et al. (2012) identified the product/service, demand, supply, information management and macro-level risk and proposed relevant risk mitigation strategies. The individual level and supply chain risks in agri-food supply chains were discussed by Leat and Revoredo-Giha (2013). Additionally, Wang et al. (2012) and Vlajic et al. (2012) proposed an aggre-gative food safety risk assessment model and framework for robust food supply chains respectively.

2.3 Research gaps and contributions

The comparison of the key relevant papers from the literature with the current study is depicted in Table 1. It can be noticed from this table that fewer scholars simultaneously considered several members, periods and modes in their studies (Gholamian and Taghan-zadeh 2017; Allaoui et al. 2018; Mogale et al. 2018a; 2019a). Facility location cost and transport cost were commonly considered in the objective function of the formulated mod-els (Etemadnia et al. 2015; Mogale et al. 2018a; Maiyar and Thakkar 2019). However, inventory cost, transit and storage loss cost, emission and risk penalty cost appeared in meagre papers. Furthermore, location-allocation and product flow decisions are frequently observed in numerous papers, but the capacity level, fleet management and food loss

Table 1 Comparison of current study with the literature

Study	Model characteristics					Objective function components							Decisions							Optimization tool
	MP	MM/IM	ME	Modelling	Country of application	FLC	TC	IC	TLC	SLC	EC	RPC	L	A	CL	FM	I	PF	FLQ	
Gholamian and Taghanzadeh (2017)	✓	✓	✓	MILP	Iran	✓	✓	✓					✓	✓	✓		✓	✓	✓	CPLEX
Jonkman et al. (2019)	✓		✓	MILP	Netherlands	✓	✓	✓					✓				✓	✓		CPLEX
Mogale et al. (2018a)	✓	✓	✓	MINLP	India	✓	✓	✓					✓	✓	✓	✓	✓	✓		NCRO and NSGA-II
Etemadnia et al. (2015)		✓	✓	MILP	US	✓	✓						✓			✓		✓		CPLEX
Asgari et al. (2013)	✓		✓	LIP	Iran		✓	✓									✓	✓		LINGO and GA
Rohmer et al. (2019)		✓	✓	LP	Netherlands		✓											✓		Epsilon constraint
Boonmee and Sethanan (2016)	✓			MIP	Thailand		✓	✓						✓		✓	✓	✓		CPLEX, GLNPSO and PSO
Mogale et al. (2019a)	✓	✓		MINLP	India	✓	✓	✓					✓			✓	✓	✓		MOPSO and NSGA-II
Ge et al. (2018)	✓		✓	MILP	US	✓	✓		✓				✓	✓	✓			✓	✓	CPLEX
Khamjan et al. (2013)	✓		✓	MILP	Thailand	✓	✓						✓	✓	✓	✓		✓		LINGO and Heuristic
Orjuela-Castro et al. (2017)			✓	MLP	Colombia	✓			✓				✓	✓				✓	✓	GAMS
Liotta et al. (2015)		✓	✓	MILP	Europe		✓				✓		✓	✓				✓		CPLEX
Ardjmand et al. (2016)			✓	MILP	US	✓	✓					✓	✓	✓				✓		CPLEX and GA

Table 1 (continued)

Study	Model characteristics					Objective function components							Decisions							Optimization tool
	MP	MM/IM	ME	Modelling	Country of application	FLC	TC	IC	TLC	SLC	EC	RPC	L	A	CL	FM	I	PF	FLQ	
Maiyar and Thakkar (2019)	✓	✓		MINLP	India	✓	✓				✓		✓					✓		PSODE
Rancourt et al. (2015)	✓			MILP	Kenya	✓	✓						✓	✓				✓		CPLEX
Present study	✓	✓	✓	MILP	India	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	CPLEX, GLNPSO and PSO

Model characteristics: *MP* Multiple period, *MM/IM* Multimodal/Intermodal, *ME* Multiple echelon, Modelling: *MILP* Mixed integer linear programming, *MIP* Mixed integer programming, *LIP* Linear integer programming, *MINLP* Mixed integer non-linear programming

Objective function components: *FLC* Facility location cost, *TC* Transportation cost, *IC* Inventory cost, *TLC* Transit loss cost, *SLC* Storage loss cost, *EC* Emission cost, *RPC* Risk penalty cost

Decisions: *L* Location, *A* Allocation, *CL* Capacity level, *FM* Fleet management, *I* Inventory, *PF* Product flows, *FLQ* Food loss quantity

quantity are hardly found in the existing studies (Orjuela-Castro et al. 2017; Boonmee and Sethanan 2016; Mogale et al. 2019a). To bridge the aforementioned research gap, firstly a multi-period single objective mathematical model is developed for a green food grain SCND problem. The model seeks to minimize the overall food grain supply chain network cost comprising of fixed cost of silo establishment, transportation, emission, inventory holding and risk penalty cost, cost of transit and storage loss of food grain. Secondly, various aspects like transit and storage loss of food grain, carbon emission and risk penalty are concurrently included in the model. Many real-life constraints pertaining to food grain supply chain are taken into consideration while formulating the model. Thirdly, a mathematical model is solved using a variant of the Particle Swarm Optimization (PSO) algorithm and original PSO due to the complex and highly constrained nature of the underline problem. The results obtained using the proposed algorithms are compared with the optimal solutions of the Cplex solver through different real-world instances. Finally, sensitivity analysis is performed to visualize the responsiveness of the formulated model and solution approach.

3 Problem overview and model formulation

It is observed from the statistics mentioned in the introduction section that there is a colossal shortage of storage capacity against the central food grain stock. To fulfil this gap, management authorities in India commenced establishing modern capacitated silos in major producing and consuming states across the country. This problem is an SCND problem comprising of five echelons, i.e. procurement centres, base and field silos, regional warehouses and destination warehouses. The strategic decision of silo location requires a large amount of capital investment for establishment (Mogale et al. 2018a). The formulated model helps in strategic and tactical decisions of food grain supply chain. The model simultaneously determines the number of silos established, shipment and storage quantity, transit and storage loss quantity and number of mixed capacitated vehicles utilized. Further, various constraints like food grain availability, demand satisfaction, inventory flow balance, multi-sourcing and distribution strategy, storage capacity constraint, vehicle capacity constraint and food grain loss calculation constraint are incorporated in the developed model.

The assumptions considered while formulating the mathematical model are described here. The notations of the model comprising of indices, parameters and decision variables are defined in "Appendix 1" due to space constraint.

Assumptions

1. Potential locations for the establishment of silos are known and fixed.
2. The procurement quantity of food grain, demand of destination warehouses and capacity of regional warehouses are specific and deterministic.
3. Three mixed capacitated vehicles with restricted accessibility are considered for food grain movement.
4. Initial inventory at the silos and regional warehouses is considered zero.
5. Full truckload scenario is considered.

Objective function

The objective function of the model is to minimize the overall food grain supply chain cost which comprises the following terms.

Base and field silo establishment and establishment risk penalty cost

$$\sum_{b,h} \left(F_b^h + \varepsilon_b^h rc \right) X_b^h + \sum_{f,j} \left(F_f^j + \varepsilon_f^j rc \right) Y_f^j. \tag{1.1}$$

Transportation, food grain transit loss and transportation risk penalty costs from procurement centre to base silo.

$$\sum_{p,b,t} \left[\left(tc_{pb} dis_{pb} U_{pb}^t \right) + \left(lcTl_{pb}^t \right) + \left(g_{pb} rc Y_{pb}^t \right) \right] \tag{1.2}$$

Transportation, food grain transit loss and transportation risk penalty costs from base to field silo.

$$\sum_{b,f,t} \left[\left(tc_{bf} dis_{bf} U_{bf}^t \right) + \left(lcTl_{bf}^t \right) + \left(g_{bf} rc Y_{bf}^t \right) \right] \tag{1.3}$$

Transportation, food grain transit loss and transportation risk penalty costs from field silo to regional warehouse.

$$\sum_{f,r,t} \left[\left(tc_{fr} dis_{fr} U_{fr}^t \right) + \left(lcTl_{fr}^t \right) + \left(g_{fr} rc Y_{fr}^t \right) \right] \tag{1.4}$$

Transportation, food grain transit loss and transportation risk penalty costs from regional warehouse to destination warehouse.

$$\sum_{r,d,t} \left[\left(tc_{rd} dis_{rd} U_{rd}^t \right) + \left(lcTl_{rd}^t \right) + \left(g_{rd} rc Y_{rd}^t \right) \right] \tag{1.5}$$

Inventory and food grain storage loss cost at base silo, field silo and regional warehouse.

$$\sum_{b,t} \left[\left(ih_b IN_b^t \right) + \left(lcSl_b^t \right) \right] + \sum_{f,t} \left[\left(ih_f IN_f^t \right) + \left(lcSl_f^t \right) \right] + \sum_{r,t} \left[\left(ih_r IN_r^t \right) + \left(lcSl_r^t \right) \right] \tag{1.6}$$

Cost of CO_2 emission

$$\left[\sum_{p,b,n_1,t} e_{pb}^{n_1} dis_{pb} V_{pb}^{n_1 t} + \sum_{b,f,n_2,t} e_{bf}^{n_2} dis_{bf} V_{bf}^{n_2 t} + \sum_{f,r,n_3,t} e_{fr}^{n_3} dis_{fr} V_{fr}^{n_3 t} + \sum_{r,d,n_4,t} e_{rd}^{n_4} dis_{rd} V_{rd}^{n_4 t} \right] ce \tag{1.7}$$

Subject to constraints

$$\sum_b U_{pb}^t \le A_p^t \quad \forall p, \forall t \tag{2}$$

Constraint (2) depicts the supply restriction of procurement centre.

$$U_{pb}^t \le Z Y_{pb}^t \quad \forall p, \forall b, \forall t \tag{3}$$

Constraint (3) illustrates that food grain quantity should be transferred to assigned base silos from procurement centres.

$$Y_{pb}^t \leq \sum_h X_b^h \quad \forall p, \forall b, \forall t \tag{4}$$

Procurement centre can transfer the shipment quantity to only established base silos and this is indicated by Constraint (4).

$$\sum_f U_{bf}^t \leq IN_b^t \quad \forall b, \forall t \tag{5}$$

Supply limit of base silo is depicted by Constraint (5).

$$U_{bf}^t \leq Z Y_{bf}^t \quad \forall b, \forall f, \forall t \tag{6}$$

Constraint (6) makes sure that base silos should transfer the food grain quantity to the assigned field silos.

$$Y_{bf}^t \leq \sum_{h,j} M_{bf}^{hj} \quad \forall b, \forall f, \forall t \tag{7}$$

$$\sum_h X_b^h + \sum_j X_f^j \geq 2 \sum_{h,j} M_{bf}^{hj} \quad \forall b, \forall f \tag{8}$$

$$\sum_h X_b^h + \sum_j X_f^j - \sum_{h,j} M_{bf}^{hj} \leq 1 \quad \forall b, \forall f \tag{9}$$

Base silo can transfer the food grain to the field silo only if both silos are established. A new binary variable M_{bf}^{hj} is inserted which becomes 1 if both X_b^h and X_f^j become 1 else remains 0. Hence, constraint set (7)–(9) fulfil the aforementioned condition.

$$\sum_r U_{fr}^t \leq IN_f^t \quad \forall f, \forall t \tag{10}$$

Constraint (10) limits the flow of food grain from field silo to regional warehouses.

$$U_{fr}^t \leq Z Y_{fr}^t \quad \forall f, \forall r, \forall t \tag{11}$$

Constraint (11) ensures that field silo should transfer the shipment quantity to the assigned regional warehouses.

$$Y_{fr}^t \leq \sum_j X_f^j \quad \forall f, \forall r, \forall t \tag{12}$$

Field silo is assigned to the regional warehouses if it is established and this is described by constraint (12).

$$\sum_d U_{rd}^t \leq IN_r^t \quad \forall r, \forall t \tag{13}$$

Constraint (13) restricts the food grain quantity transferred from regional to destination warehouses.

$$U_{rd}^t \le Z\, Y_{rd}^t \quad \forall r, \forall d, \forall t \tag{14}$$

Constraint (14) guarantee that regional warehouses transferred the food grain quantity to assigned destination warehouses.

$$\sum_r U_{rd}^t = L_d^t \quad \forall d, \forall t \tag{15}$$

Demand satisfaction constraint is represented by constraint (15).

$$IN_b^{t-1} + \sum_p U_{pb}^t - \sum_f U_{bf}^t - Sl_b^t = IN_b^t \quad \forall b, \forall t \tag{16}$$

$$IN_f^{t-1} + \sum_b U_{bf}^t - \sum_r U_{fr}^t - Sl_f^t = IN_f^t \quad \forall f, \forall t \tag{17}$$

$$IN_r^{t-1} + \sum_f U_{fr}^t - \sum_d U_{rd}^t - Sl_r^t = IN_r^t \quad \forall r, \forall t \tag{18}$$

The inventory balance equation for base silo, field silo and regional warehouse are represented by Constraints (16)–(18).

$$IN_b^t \le \sum_h cb_h X_b^h \quad \forall b, \forall t \tag{19}$$

$$IN_f^t \le \sum_j cf_j X_f^j \quad \forall f, \forall t \tag{20}$$

$$IN_r^t \le cr_r \quad \forall r, \forall t \tag{21}$$

Constraint set (19)–(21) enforces the capacity constraints for base silo, field silo and regional warehouses.

$$\sum_h X_b^h \le 1 \quad \forall b \tag{22}$$

$$\sum_j X_f^j \le 1 \quad \forall f \tag{23}$$

Furthermore, constraint set (22), (23) makes sure that at each potential locations of base and field silo at most one type of base and field silos are to be established.

$$U_{pb}^t \le \sum_{n_1} cv_{n_1} V_{pb}^{n_1 t} \quad \forall p, \forall b, \forall t \tag{24}$$

$$U_{bf}^t \le \sum_{n_2} cv_{n_2} V_{bf}^{n_2 t} \quad \forall b, \forall f, \forall t \tag{25}$$

$$U_{fr}^{t} \leq \sum_{n_3} cv_{n_3} V_{fr}^{n_3 t} \quad \forall f, \forall r, \forall t \tag{26}$$

$$U_{rd}^{t} \leq \sum_{n_4} cv_{n_4} V_{rd}^{n_4 t} \quad \forall r, \forall d, \forall t \tag{27}$$

The vehicle capacity restrictions for each stage are defined by Constraint (24)–(27).

$$\sum_{b} V_{pb}^{n_1 t} \leq nv_{n_1 p}^{t} \quad \forall p, \forall n_1, \forall t \tag{28}$$

$$\sum_{f} V_{bf}^{n_2 t} \leq nv_{n_2 b}^{t} \quad \forall b, \forall n_2, \forall t \tag{29}$$

$$\sum_{r} V_{fr}^{n_3 t} \leq nv_{n_3 f}^{t} \quad \forall f, \forall n_3, \forall t \tag{30}$$

$$\sum_{d} V_{rd}^{n_4 t} \leq nv_{n_4 r}^{t} \quad \forall r, \forall n_4, \forall t \tag{31}$$

The four constraints (28)–(31) indicate that the number of utilized vehicles between given two echelons should be less than or equal to their availability.

$$Tl_{pb}^{t} = lb U_{pb}^{t} \quad \forall p, \forall b, \forall t \tag{32}$$

$$Tl_{bf}^{t} = lb U_{bf}^{t} \quad \forall b, \forall f, \forall t \tag{33}$$

$$Tl_{fr}^{t} = lb U_{fr}^{t} \quad \forall f, \forall r, \forall t \tag{34}$$

$$Tl_{rd}^{t} = lj U_{rd}^{t} \quad \forall r, \forall d, \forall t \tag{35}$$

The four constraints illustrated by Eqs. (32)–(35) are used to compute the fraction of the shipment quantity that lost during transit from procurement centre to base silo, base silo to field silo, field silo to regional warehouse and regional to destination warehouse.

$$Sl_{b}^{t} = ls IN_{b}^{t} \quad \forall b, \forall t \tag{36}$$

$$Sl_{f}^{t} = ls IN_{f}^{t} \quad \forall f, \forall t \tag{37}$$

$$Sl_{r}^{t} = lw IN_{r}^{t} \quad \forall r, \forall t \tag{38}$$

Moreover, the fraction of inventory stock that lost at base silo, field silo and regional warehouses are calculated using the Constraints set (36)–(38).

$$X_{b}^{h}, X_{f}^{j}, Y_{pb}^{t}, Y_{bf}^{t}, Y_{fr}^{t}, Y_{rd}^{t} \in \{0, 1\} \quad \forall p, \forall b, \forall f, \forall r, \forall d, \forall h, \forall j, \forall t \tag{39}$$

$$U_{pb}^{t}, U_{bf}^{t}, U_{fr}^{t}, U_{rd}^{t}, Tl_{pb}^{t}, Tl_{bf}^{t}, Tl_{fr}^{t}, Tl_{rd}^{t},$$
$$IN_{b}^{t}, IN_{f}^{t}, IN_{r}^{t}, Sl_{b}^{t}, Sl_{f}^{t}, Sl_{r}^{t} \geq 0 \quad \forall p, \forall b, \forall f, \forall r, \forall d, \forall t \tag{40}$$

$$V_{pb}^{n_1 t}, V_{bf}^{n_2 t}, V_{fr}^{n_3 t}, V_{rd}^{n_4 t} \in \mathbb{Z}^{+} \quad \forall p, \forall b, \forall f, \forall r, \forall d, \forall n_1, \forall n_2, \forall n_3, \forall t \tag{41}$$

Finally, Constraints set (39)–(41) represent the binary, non-negativity and integer restrictions, respectively.

The supply chain network configuration of the current problem depends on a number of echelons involved and time period. The formulated model has more variables, parameters and real-life constraints compared with the normal SCND problem. All these variables, parameters and constraints increase exponentially as the supply chain network configuration grows. Due to the inherent complexity and a large number of variables as well as constraints of the underline problem, many authors addressed these types of complex problems by means of heuristics and metaheuristics algorithms in extant literature (Khalifehzadeh et al. 2015; Hamadani et al. 2013; Eskandarpour et al. 2017; De et al. 2019; Zhu et al. 2009; Zhao and Dou 2011; Mogale et al. 2018a; b; Naderi et al. 2019).

4 Solution methods

In the domain of evolutionary and swarm intelligence algorithms, many researchers developed the various variant of existing algorithms to solve the complicated real-life problems. Metaheuristics are receiving more attention to solve complex agricultural supply chain problems (Aliano Filho et al. 2019; Florentino et al. 2020; Chan et al. 2020). Recently, several new variants of PSO algorithm were employed to deal with the SCND problem (Maiyar and Thakkar 2019; Soleimani and Kannan 2015; Yamada and Febri 2015). However, in most cases, premature convergence or the trapping in local optimal solution found as a major challenge of PSO and its variants. An extended version of PSO with combined global best, local best and neighbour best social structures called GLNPSO was developed by Pongchairerks and Kachitvichyanukul (2009) to improve the performance of traditional PSO. Several authors proved its dominance over the other evolutionary algorithms and PSO variants (Boonmee and Sethanan 2016; Chan et al. 2020; Wisittipanich and Hengmeechai 2017; Xu et al. 2011) However, food grain supply chain problems were not addressed through the GLNPSO. Thus, we have tackled the integrated multi-echelon and multi-period SCND problem using GLNPSO and compared the results with original PSO and Cplex. The exhaustive explanation of the proposed two algorithms is given in the next two subsections.

4.1 Particle swarm optimization

Particle swarm optimization is a population-based random search method based on social and cognitive principles (Eberhart and Kennedy 1995). It was stimulated by the behaviour of birds flocking or behaviour of fish schooling. In PSO, a particle is used to denote the solution of the specific problem and it has two main features: position and velocity. The swarm comprises of a population of particles which are intelligently initialized. These particles fly over the solution search space for finding out the global optima of an underline problem by updating generations. While attaining the better position, every particle tries to utilize the cognitive

information of its experiences and the social information of the swarm. Initially, the fitness function value of each particle is determined by evaluating every particle in the population. Then, the personal best position (pbest) of the specific particle is updated if the objective function of the new position is better than the previous position. Similarly, the global best position (gbest) is updated if any new position with better objective function than the previous best objective function of the whole swarm is revealed by any particle in the group. Each particle reaches the new position from its current position with the help of updated velocity. The procedure will be stopped once the predefined termination criteria are satisfied. Then, the near-optimal solution of the best particle obtained until now is selected as the solution to the problem. The following Eqs. (42) and (43) are utilized to update the velocity and position of every particle respectively.

$$\lambda_{ih}(\tau + 1) = w(\tau)\lambda_{ih}(\tau) + c_p r_1 \left[\varepsilon_{ih}^{best}(\tau) - \theta_{ih}(\tau)\right] + c_g r_2 \left[\varepsilon_{gh}^{best}(\tau) - \theta_{ih}(\tau)\right] \quad (42)$$

$$\theta_{ih}(\tau + 1) = \theta_{ih}(\tau) + \lambda_{ih}(\tau + 1) \quad (43)$$

Here, $\lambda_{ih}(\tau)$ and $\theta_{ih}(\tau)$ denote the velocity and position of the ith particle at the hth dimension in the τth iteration. Next, w, c_p and c_g are used to depict the inertia, cognitive and social coefficients respectively. The personal best positon and global best position of ith particle at the hth dimension in the τth iteration are represented by $\varepsilon_{ih}^{best}(\tau)$ and $\varepsilon_{gh}^{best}(\tau)$ respectively. The random numbers r_1 and r_2 are uniformly distributed in the range of [0, 1].

4.2 GLNPSO

The GLNPSO algorithm is an extended variant of PSO proposed by Pongchairerks and Kachitvichyanukul (2009) to enhance the performance of traditional PSO. The multiple social learning terms are used in the velocity updating formula instead of single global knowledge and every particle communicate with several particular subsets of the swarm for performance improvement. To update the velocity, this algorithm uses the local best and near neighbour best social structure in addition to the personal best and global best position. This leads to diminish the issue of premature convergence, enhance the diversification of particles in the solution space and govern the particles through various features of swarm information. The best position found by any particle among the numerous adjacent particles is known as local best position (lbest). Therein, initially, the several sub-swarms with the population size of N are generated by dividing the whole swarm and the local best particle is chosen among these K neighbouring particles. Similarly, particles near neighbour best (nbest) position introduced by Veeramachaneni et al. (2003) is a social learning behaviour concept which is calculated using the fitness-distance-ratio (FDR). The near neighbour best position describes the interaction among the particles to obtain a better quality solution. The GLNPSO uses five terms including current velocity, personal best position, global best position, local best position and near neighbour best position while updating the particle velocity for the next iteration. The modified formula for updating the velocity and position is given as follows

$$\begin{aligned} \lambda_{ih}(\tau + 1) = {} & w(\tau)\lambda_{ih}(\tau) + c_p r_1 \left[\varepsilon_{ih}^{best}(\tau) - \theta_{ih}(\tau)\right] + c_g r_2 \left[\varepsilon_{gh}^{best}(\tau) - \theta_{ih}(\tau)\right] \\ & + c_l r_3 \left[\varepsilon_{ih}^{lbest}(\tau) - \theta_{ih}(\tau)\right] + c_n r_4 \left[\varepsilon_{ih}^{nbest}(\tau) - \theta_{ih}(\tau)\right] \end{aligned} \quad (44)$$

$$\theta_{ih}(\tau + 1) = \theta_{ih}(\tau) + \lambda_{ih}(\tau + 1) \qquad (45)$$

where $\varepsilon_{ih}^{lbest}(\tau)$ and $\varepsilon_{ih}^{nbest}(\tau)$ illustrate the local and near neighbour best position of the ith particle at the hth dimension in the τth iteration. The acceleration constants of local and near neighbour best position are represented by c_l and c_n. The r_3 and r_4 are uniformly distributed random numbers in the range of [0, 1]. The meaning of other parameters is similar to the Eqs. (42) and (43). Readers are requested to refer Pongchairerks and Kachitvichyanukul (2009) for exhaustive information and performance of GLNPSO over the existing variants of PSO. The proposed algorithm is correspondingly transformed to match the present scenario of food grain supply chain problem. The initialisation, iteration and termination stages are implemented step by step as shown in Fig. 2. In the initialization stage, initially, the various inputs like model parameters values, the objective function, constraints and tuned algorithmic control parameters are provided to the algorithm. During the iteration stage, each particle moves to another position using its velocity and determines the various potential solutions of the problem. Particles cognitive and social information encompassing of personal best, global best, local best and near neighbour best positions are updated. Next, the velocity and position of all the particles are updated using the Eqs. (44) and (45). Finally, the algorithm will be stopped when it reaches the predefined termination criterion.
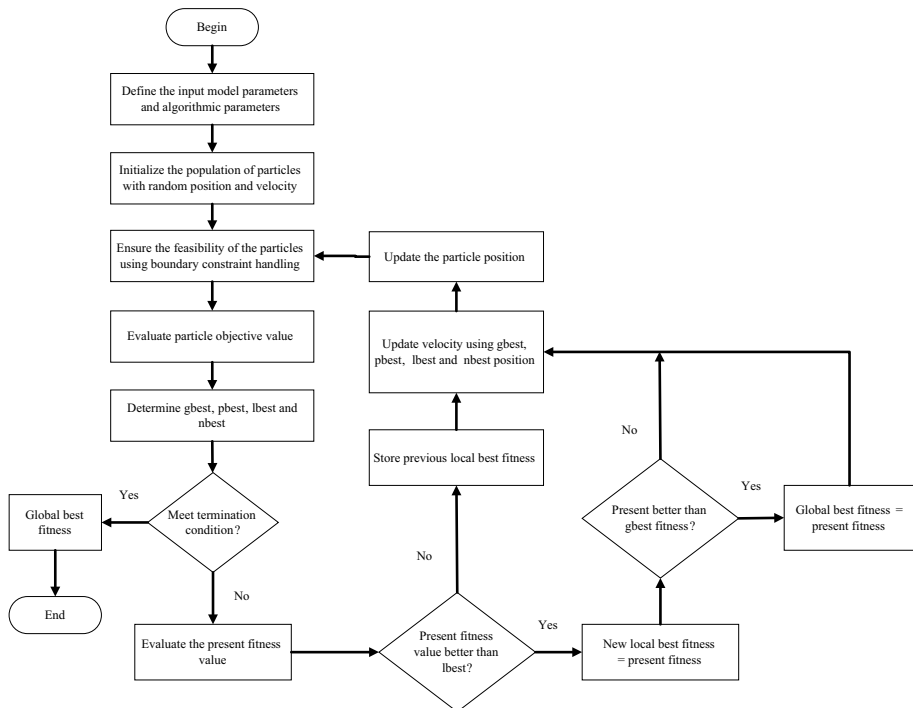

Fig. 2 Flow diagram for GLNPSO implementation

5 Computational experiments

5.1 Problem instances and data collection

The geographically widespread main wheat surplus and deficit states in India are considered for this research study. The essential data is gleaned from field survey and many reliable sources like CAG report 2013, PDS Portal of India, High-level committee report 2015 and FCI portal. Following the gleaned data, fifteen real-life problem instances are solved to validate the formulated model. The number of decision variables present in the problem instance decides the problem complexity and in this paper, the time period is the decisive factor which controls the total decision variables. Therefore, all the considered problem instances are categorized into the small scale, medium scale and large scale problems based on time period. As per this classification, the categorized problem sets are mentioned in Table 2. Also, the characteristics of each type of problem instance comprising of a total number of variables and constraints are described in the same table.

5.2 Parameter setting

The parameter tuning of the metaheuristic algorithm is one of the vital element in obtaining the better near-optimal solution of the problem (Mogale et al. 2018a, 2019a). The important parameters of GLNPSO include inertia weight (w), number of adjacent neighbours (k), acceleration constants for pbest, gbest, lbest and nbest positions, population size and maximum iterations. To verify all the promising combinations of all algorithmic control parameters is practically quite difficult. Hence, the suitable algorithmic parameters which provide the better results are carefully chosen based on the several preliminary computational experiments and analysis of the proposed algorithm. Following are the values of tuned control parameter utilized in proposed algorithms. Population size: 100, Maximum iteration = 200, Inertia weight: 0.9, Number of adjacent neighbours = 5, pbest, gbest, lbest and nbest = 1.

5.3 Solving the problem instances and analysing the results

Initially, we have attempted to solve all the problem instances using Cplex optimization solver and obtain the optimal solutions to the problems. However, Cplex solver optimally solved only small size problem instances and goes out of memory after taking the large computational time while resolving medium and large size problem instances. If Cplex exhibits the out of memory problem for particular instance then the best known objective function value (total cost) is taken into account. Hence, two competitive metaheuristic algorithms involving GLNPSO and PSO are utilized to solve these problem instances. The MATLAB R2018a is used for coding of GLNPSO and PSO algorithm and codes are executed on the platform of Intel Core i5 2.90 GHz processor with 8 GB RAM under Windows 8 environment. To obtain the values of decision variables, initially, all problem instances are solved employing GLNPSO with calibrated parameter values. Further, the PSO algorithm with the identical population size and iterations is implemented to validate the results obtained through GLNPSO. Due to the random search nature of the proposed algorithms, twenty runs of each instance are carried out and its results are shown in Table 3. This table depicts the computational results which include the minimum, average

Table 2 Problem instances and associated variables and constraint

Problem category	Problem number	Instance code (P-B-F-R-D-T)	P	B	F	R	D	T	Decision variables	Constraints
Small scale	1	3-2-3-4-6-3	3	2	3	4	6	3	927	1711
	2	7-3-4-8-10-3	7	3	4	8	10	3	3143	5501
	3	10-5-6-12-13-3	10	5	6	12	13	3	5703	9734
	4	12-6-7-14-15-3	12	6	7	14	15	3	8134	13,832
	5	14-8-10-17-20-3	14	8	10	17	20	3	13,321	22,469
Medium scale	6	17-10-13-20-24-6	17	10	13	20	24	6	40,189	67,370
	7	21-13-16-22-27-6	21	13	16	22	27	6	52,039	87,168
	8	23-14-17-23-28-6	23	14	17	23	28	6	58,127	97,408
	9	25-15-18-24-30-6	25	15	18	24	30	6	65,439	109,554
	10	27-16-19-26-31-6	27	16	19	26	31	6	74,095	123,920
Large scale	11	30-18-21-27-33-9	30	18	21	27	33	9	129,567	216,669
	12	35-20-25-32-40-9	35	20	25	32	40	9	185,113	308,513
	13	38-21-26-33-45-9	38	21	26	33	45	9	200,627	332,681
	14	40-22-28-35-50-9	40	22	28	35	50	9	247,425	411,155
	15	50-25-30-45-60-9	50	25	30	45	60	9	328,605	538,795

Table 3 Computational results obtained through GLNPSO, PSO and CPLEX for all problem instances

Problem number	GLNPSO (Mn Rs)					PSO (Mn Rs)					CPLEX (Mn Rs)	
	Min. solution	Average solution	Max. solution	SD	CPU time (s)	Min. solution	Average solution	Max. solution	SD	CPU time (s)	Solution	CPU time (s)
1	603.72	615.85	642.71	10.48	359.73	615.39	626.63	656.02	12.82	352.6	588.35	8.0
2	846.73	859.03	879.08	11.01	736.15	860.89	885.49	916.51	15.39	725.21	811.35	10.89
3	1407.31	1450.82	1510.76	26.97	820.52	1438.07	1480.40	1540.59	29.60	818.52	1386.59	15.62
4	1710.19	1742.17	1766.94	17.78	1095.07	1743.82	1785.67	1823.56	22.72	1077.5	1682.18	40.64
5	3152.70	3173.03	3206.20	17.21	1581.94	3234.66	3263.56	3285.09	19.64	1542.03	3103.30	480.12
6	3806.00	3968.63	4420.00	182.24	2857.73	3553.33	4052.50	4660.33	274.59	2813.75	3704.64	22,035.05*
7	4809.46	4913.41	5171.08	96.62	3735.18	4941.89	5104.84	5275.95	106.59	3688.12	4650.00	50,385.34*
8	5568.65	5680.86	5823.78	81.86	4270.45	5686.41	5783.99	6120.27	156.51	4254.85	5262.30	115,173.00*
9	6284.72	6401.65	6616.67	111.10	5162.08	6479.17	6632.03	6844.72	115.94	5103.37	6115.80	39,610.56*
10	5889.69	6190.57	6391.36	189.28	5683.95	6171.56	6302.40	6871.56	193.48	5540.48	5782.40	86,377.90*
11	7865.49	8077.82	8341.92	167.66	5990.16	7967.89	8235.96	8543.83	185.18	5891.93	7570.90	64,752.32*
12	9818.59	10,050.27	10,162.79	103.56	7813.84	10,010.60	10,170.92	10,357.82	131.59	7684.35	9606.00	72,165.20*
13	11,326.27	11,846.56	12,031.69	210.82	9305.49	11,368.28	11,888.44	12,128.58	216.23	8919.73	11,067.00	37,856.48*
14	13,022.91	13,832.56	14,091.78	428.92	10,654.71	13,225.35	13,905.74	14,439.35	443.95	10,185.2	12,783.00	75,426.95*
15	16,000.75	16,493.98	16,954.50	309.60	12,129.82	16,054.50	16,665.88	17,215.00	362.13	11,554.3	15,921.00	133,262.71*

*Total running time of CPLEX before it is aborted due to out of memory condition

and maximum objective function value obtained after the twenty runs of each algorithm for each instance. The standard deviation and computational time required for each algorithm are also presented in this table. Convergence graphs of both algorithms for problem instance four is illustrated in Fig. 3.

It is observed from Table 3 that the GLNPSO provides better results than traditional PSO for all considered problem instances with slightly higher computational time. The steady functioning of the suggested two algorithms in twenty runs is noticed through the standard deviation and is also given in Table 3. The marginally lower standard deviation of GLNPSO for all fifteen problem instances is easily perceived from this table. Thus, we can say that the solution obtained in each replication is a near-optimal solution to the underline problem. The better convergence behaviour of GLNPSO compared to traditional PSO is observed from Fig. 3. It means that GLNPSO requires less number of iterations for finding out the near-optimal solution. The computational results presented in this section demonstrate the better performance of GLNPSO over traditional PSO.

5.4 Sensitivity analysis

The officials working in the government agencies need to understand or envisage the trends or patterns in the solutions after the parameter variations. Hence, the effect of paramount model parameters encompassing a total number of destination warehouses, procurement centres and storage capacities of silos are evaluated on instance four by changing their values. This analysis will be helpful to many administrators of government agencies and other private bodies engaged in food grain supply chain activities whenever parameters obtain values with more or less than the current values.
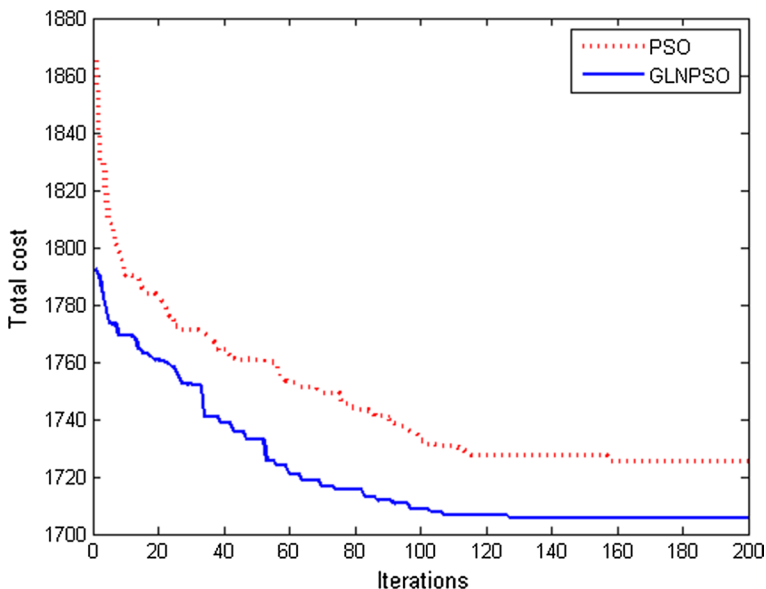

Fig. 3 Convergence graph of two algorithms

5.4.1 The influence of number of destination warehouses, procurement centres and silo's capacity

The number of destination warehouses (DW), procurement centres (PC) and silo's capacity (SCAP) are varied in the range of $[-50\%, +50\%]$ of their current values and its effect on the total supply chain cost is portrayed in Fig. 4. It can be realized from this figure that the total cost upsurges and diminishes after the escalation and reduction of destination warehouses and procurement centres, respectively. The total cost is reduced and augmented by 29.20% and 66.51% when the destination warehouses diminished and increased by 50% from its current value. Correspondingly, we obtained the graph with similar characteristics but with different numerical values after the variation of -50% to $+50\%$ from its current value of the number of procurement centres and it is depicted in the same figure. Due to the augmentation of silo's capacity, the establishment cost increased and transportation along with emission cost decreased. However, the proportion increase in establishment costs is lower than the proportion decrease in transportation and emission costs. Thus, the total supply chain cost is decreased after the establishment of new silos which is shown in Fig. 4.

6 Conclusion and scope of future research work

This paper has dealt with the green food grain SCND problem in India. The multi-period single objective mathematical model is formulated to minimize the total cost and optimizes supply chain design decisions. The mathematical model is solved using two population-based random search algorithms (GLNPSO and PSO) because of the high complexity of the model. The numerous realistic problem instances considering the key Indian wheat producing and consuming states are solved by means of proposed two algorithms. The obtained results are validated by comparing with exact solutions. The computational results
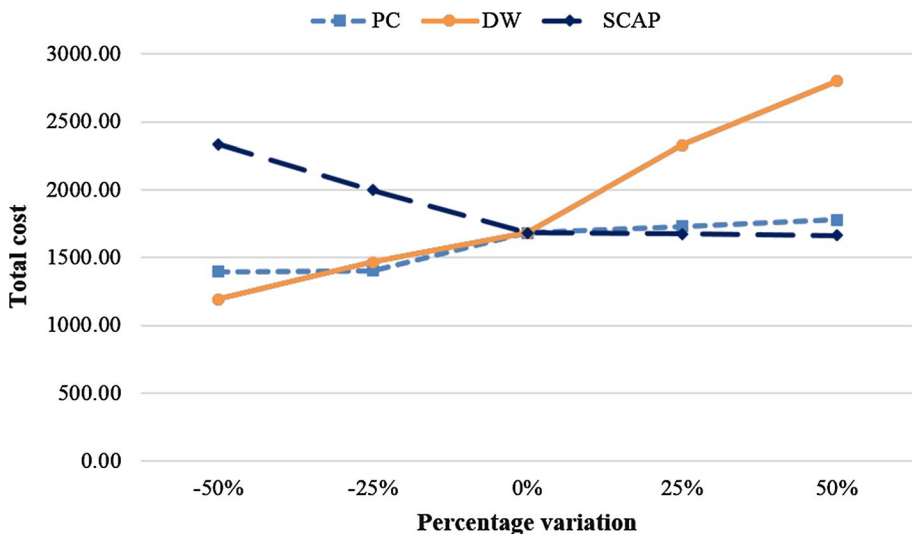

Fig. 4 The sensitivity analysis results

obtained through the GLNPSO is better than the traditional PSO with slightly higher CPU time for all problem instances. The sensitivity analysis is carried out by considering three paramount parameters to observe the influence of them on the model solution. The managerial insights acquired through this research work would be valuable to several management authorities, state government agencies, railways and other administrative bodies connected with food grain supply chain for their management activities.

6.1 Contributions to theory and practice

This research study provides multiple insights to the theory and practice. Lack of integration and quantification of post-harvest losses and risks in the food supply chains is evident from extant literature (Hosseini-Motlagh et al. 2019; Maiyar and Thakkar 2019; Ge et al. 2018; Mogale et al. 2019a; Ketzenberg et al. 2015). Majority of the existing studies on food supply chains are carried out in the developed countries and the developing nations mainly focused on satisfying the need of rising population and ignored the environmental aspect (Shukla and Jharkharia 2013; Soto-Silva et al. 2016). The decision support models considering the finite planning horizon and SCND issues in emerging economies need to be formulated to improve the food supply chain performance (Esteso et al. 2018; Zhu et al. 2018). The finite number of mixed capacitated vehicles are included which overlooked in the work of Asgari et al. (2013). The limited number of studies conducted the comparative analysis of metaheuristic algorithms for food supply chain problems (Allaoui et al. 2018; Mohammed and Wang 2017; Esteso et al. 2018).

The various members in food grain supply chain such as government agencies, railways, and other private service providers can obtain beneficial and essential managerial insights from this research work. Policymakers can conduct the feasibility analysis of multiple possible candidate locations of silos through the formulated model to evade the significant loss of initial capital investment. A solution of the model provides the number of mixed capacitated vehicles utilized for shipment which can be helpful for transportation planning. The time-dependent movement plan of food grain stock can be used for scheduling of various mixed capacitated vehicles which reduces the demurrage charges associated with vehicles. The capacity of current warehouses can be suitably utilized through the well-organized inventory storage plan. This will be helpful to curb the post-harvest losses and speedy movement of food grain from production to consumption regions. To curb the excess inventory cost, management authorities can fix the operational and buffer stock norms following the proposed model. The parentage of food grain loss during bulk transportation and storage is less than the conventional method of gunny bags. Due to this little food grain losses, policymakers should transform all the conventional activities into the bulk grain operations. Moreover, rail mode of transportation can be used instead of road mode for reduction of transportation cost.

6.2 Limitations and future scope

Similar to other studies, the current research work has a few limitations which suggest the prospective areas for future examination. The stochastic procurement and demand can be incorporated into the current mathematical model to deal with uncertain scenarios. In the same way, the focus on backlog and shortages are the additional two possible ways of

development of a future model. This study can be extended towards the triple bottom line with the inclusion of social costs, farmer's growth, public health and employment creation. Additionally, the relaxation of capacity levels of silos will be another future path for the research. In this study, we assumed that the set of potential sites for the establishment of silos are well-known. Although, it may be possible that policymakers take support for finding out these set of potential sites. Multi-food grain commodities, perishability aspects and economics of scale in transportation are the further avenues to continue this research study. The maximization of food quality level and minimization of delivery time can be added in the present model to develop the multi-objective formulation.

Appendix 1

Indices

p	Index for procurement centres, $p = 1, 2, \ldots, P$
b	Index for a potential location of base silos, $b = 1, 2, \ldots, B$
f	Index for a potential location of field silos, $f = 1, 2, \ldots, F$
r	Index for regional warehouse, $r = 1, 2, \ldots, R$
d	Index for destination warehouse, $d = 1, 2, \ldots, D$
t	Index for time period $t = 1, 2, \ldots, T$
h	Index for capacity of base silo, $h = 1, 2, \ldots, H$
j	Index for capacity of field silo, $j = 1, 2, \ldots, J$
n_1	Index for truck type present at procurement centre, $n_1 = 1, 2, \ldots, N_1$
n_2	Index for rake type present at base silo, $n_2 = 1, 2, \ldots, N_2$
n_3	Index for truck type present at field silo, $n_3 = 1, 2, \ldots, N_3$
n_4	Index for truck type present at regional warehouse, $n_4 = 1, 2, \ldots, N_4$

Model parameters

Cost parameters

F_b^h	Fixed cost of establishing the base silo with capacity h at location b
F_f^j	Fixed cost of establishing the field silo with capacity j at location f
tc_{pb}	Transportation cost from procurement centre p to base silo b (per MT per km)
tc_{bf}	Transportation cost from base silo b to field silo f (per MT per km)
tc_{fr}	Transportation cost from field silo f to regional warehouse r (per MT per km)
tc_{rd}	Transportation cost from regional warehouse r to destination warehouse d (per MT km)
ih_b	Inventory holding cost at base silo b (per MT per period)
ih_f	Inventory holding cost at field silo f (per MT per period)
ih_r	Inventory holding cost at regional warehouse r (per MT per period)
lc	Food grain lost cost (per MT)
ce	Cost of ton of carbon dioxide emission
rc	Risk penalty cost

Distance parameters

dis_{pb}	Distance between procurement centre p to base silo b
dis_{bf}	Distance between base silo b to field silo f
dis_{fr}	Distance between field silo f to regional warehouse r
dis_{rd}	Distance between regional warehouse r to destination warehouse d

Vehicle related parameters

cv_{n_1}	Capacity of truck type n_1
cv_{n_2}	Capacity of rake type n_2
cv_{n_3}	Capacity of truck type n_3
cv_{n_4}	Capacity of truck type n_4
$nv_{n_1 p}^t$	Total number of n_1 type trucks available at procurement centre p in period t
$nv_{n_2 b}^t$	Total number of n_2 type rakes available at base silo b in period t
$nv_{n_3 f}^t$	Total number of n_3 type trucks available at field silo f in period t
$nv_{n_4 r}^t$	Total number of n_4 type trucks available at regional warehouse r in period t

Procurement, demand, capacity and percentage of loss parameters

A_p^t	Amount of food grain quantity available at procurement centre p in period t
L_d^t	Demand of food grain of destination warehouse d in period t
cb_h	Capacity of base silo type h
cf_j	Capacity of field silo type j
cr_r	Capacity of regional warehouse r
lb	Transit loss of food grain if transported in bulk form
lj	Transit loss of food grain if transported using conventional way of jute bags
ls	Storage loss of food grain if stored in silos
lw	Storage loss of food grain if stored in conventional warehouses

Emission parameters

$e_{pb}^{n_1}$	Amount of CO_2 released per unit distance for each n_1 type of truck travelling from procurement centre p to base silo b
$e_{bf}^{n_2}$	Amount of CO_2 released per unit distance for each n_2 type of rake travelling from base silo b to field silo f
$e_{fr}^{n_3}$	Amount of CO_2 released per unit distance for each n_3 type of truck travelling from field silo f to regional warehouse r
$e_{rd}^{n_4}$	Amount of CO_2 released per unit distance for each n_4 type of truck travelling from regional warehouse r to destination warehouse d

Risk related parameters

ϵ_b^h	Establishment risk of locating base silo with size h at potential location b
ϵ_f^j	Establishment risk of locating field silo with size j at potential location f
g_{pb}	Risk of transportation between procurement centre p to base silo b
g_{bf}	Risk of transportation between base silo b to field silo f
g_{fr}	Risk of transportation between field silo f to regional warehouse r
g_{rd}	Risk of transportation between regional warehouse r to destination warehouse d

Decision variables

Binary variables

X_b^h	1, if base silo type h is selected to be established at location b
	0 Otherwise
X_f^j	1, if field silo type j is selected to be established at location f
	0 Otherwise
Y_{pb}^t	1, if procurement centre p is assigned to base silo b in time period t
	0, Otherwise
Y_{bf}^t	1, if base silo b is assigned to field silo f in time period t
	0, Otherwise
Y_{fr}^t	1, if field silo f is assigned to regional warehouse r in time period t
	0, Otherwise
Y_{rd}^t	1, if regional warehouse r is assigned to destination warehouse d in time period t
	0, Otherwise

Continuous variables

U_{pb}^t	Shipment quantity from procurement p to base silo b in period t
U_{bf}^t	Shipment quantity from base silo b to field silo f in period t
U_{fr}^t	Shipment quantity from field silo f to regional warehouse r in period t
U_{rd}^t	Shipment quantity from regional warehouse r to destination warehouse d in period t
Tl_{pb}^t	Fraction of shipment quantity that loss from procurement p to base silo b in period t
Tl_{bf}^t	Fraction of shipment quantity that loss from base silo b to field silo f in period t
Tl_{fr}^t	Fraction of shipment quantity that loss from field silo f to regional warehouse r in period t
Tl_{rd}^t	Fraction of shipment quantity that loss from regional warehouse r to destination warehouse d in period t
IN_b^t	Inventory in base silo b at the end of period t
IN_f^t	Inventory in field silo f at the end of period t
IN_r^t	Inventory in regional warehouse r at the end of period t
Sl_b^t	Fraction of inventory stock that loss in period t at base silo b
Sl_f^t	Fraction of inventory stock that loss in period t at field silo f
Sl_r^t	Fraction of inventory stock that loss in period t at regional warehouse r

Integer variables

$V_{pb}^{n_1 t}$ Number of n_1 type of vehicles used from procurement centre p to base silo b in time period t

$V_{bf}^{n_2 t}$ Number of n_2 type of rakes used from base silo b to field silo f in time period t

$V_{fr}^{n_3 t}$ Number of n_3 type of vehicles used from field silo f to regional warehouse r in time period t

$V_{rd}^{n_4 t}$ Number of n_4 type of vehicles used from regional warehouse r to destination warehouse d in time period t

References

Akkerman, R., Farahani, P., & Grunow, M. (2010). Quality, safety and sustainability in food distribution: A review of quantitative operations management approaches and challenges. *OR Spectrum, 32*(4), 863–904.

Alagusundaram, K. (2016). Should India consider shifting to bulk food grain storage system?—A conceptual frame work. In *Proceedings of the 10th International Conference on Controlled Atmosphere and Fumigation in Stored Products (CAF2016), CAF Permanent Committee Secretariat, Winnipeg, Canada* (pp. 431–437).

Aliano Filho, A., de Oliveira Florentino, H., Pato, M. V., Poltroniere, S. C., & da Silva Costa, J. F. (2019). Exact and heuristic methods to solve a bi-objective problem of sustainable cultivation. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03468-9.

Allaoui, H., Guo, Y., Choudhary, A., & Bloemhof, J. (2018). Sustainable agro-food supply chain design using two-stage hybrid multi-objective decision-making approach. *Computers & Operations Research, 89,* 369–384.

An, K., & Ouyang, Y. (2016). Robust grain supply chain design considering post-harvest loss and harvest timing equilibrium. *Transportation Research Part E: Logistics and Transportation Review, 88,* 110–128.

Arabani, A. B., & Farahani, R. Z. (2012). Facility location dynamics: An overview of classifications and applications. *Computers & Industrial Engineering, 62*(1), 408–420.

Ardjmand, E., Young, W. A., Weckman, G. R., Bajgiran, O. S., Aminipour, B., & Park, N. (2016). Applying genetic algorithm to a new bi-objective stochastic model for transportation, location, and allocation of hazardous materials. *Expert Systems with Applications, 51,* 49–58.

Asgari, N., Farahani, R. Z., Rashidi-Bajgan, H., & Sajadieh, M. S. (2013). Developing model-based software to optimise wheat storage and transportation: A real-world application. *Applied Soft Computing Journal, 13*(2), 1074–1084.

Banasik, A., Kanellopoulos, A., Claassen, G. D. H., Bloemhof-Ruwaard, J. M., & van der Vorst, J. G. (2017). Assessing alternative production options for eco-efficient food supply chains using multi-objective optimization. *Annals of Operations Research, 250*(2), 341–362.

Bilgen, B., & Ozkarahan, I. (2007). A mixed-integer linear programming model for bulk grain blending and shipping. *International Journal of Production Economics, 107*(2), 555–571.

Boonmee, A., & Sethanan, K. (2016). A GLNPSO for multi-level capacitated lot-sizing and scheduling problem in the poultry industry. *European Journal of Operational Research, 250*(2), 652–665.

Chan, F. T., Wang, Z. X., Goswami, A., Singhania, A., & Tiwari, M. K. (2020). Multi-objective particle swarm optimisation based integrated production inventory routing planning for efficient perishable food logistics operations. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2019.1701209.

Chauhan, A., Kaur, H., Yadav, S., & Jakhar, S. K. (2019). A hybrid model for investigating and selecting a sustainable supply chain for agri-produce in India. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03190-6.

De, A., Mogale, D. G., Zhang, M., Pratap, S., Kumar, S. K., & Huang, G. Q. (2019). Multi-period multi-echelon inventory transportation problem considering stakeholders behavioural tendencies. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2019.107566.

Department of Food & Public Distribution, Ministry of Consumer affairs, Food & Public Distribution. PDS Portal of India. Retrieved February 17, 2017, from http://www.pdsportal.nic.in/main.aspx/.

Department of Food & Public Distribution, Ministry of Consumer Affairs, Food & Public Distribution. Public Distribution, NFSA & Computerisation. Retrieved February 5, 2017, from http://dfpd.nic.in/nfsa-act.htm.

Diabat, A., Govindan, K., & Panicker, V. V. (2012). Supply chain risk management and its mitigation in a food industry. *International Journal of Production Research, 50*(11), 3039–3050.

Dora, M., Wesana, J., Gellynck, X., Seth, N., Dey, B., & De Steur, H. (2019). Importance of sustainable operations in food loss: Evidence from the Belgian food processing industry. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03134-0.

Eberhart, R., & Kennedy, J. (1995.). A new optimizer using particle swarm theory.In *MHS'95. Proceedings of the sixth international symposium on micro machine and human science* (pp. 39–43).

Eskandarpour, M., Dejax, P., Miemczyk, J., & Péton, O. (2015). Sustainable supply chain network design: An optimization-oriented review. *Omega, 54,* 11–32.

Eskandarpour, M., Dejax, P., & Péton, O. (2017). A large neighborhood search heuristic for supply chain network design. *Computers & Operations Research, 80,* 23–37.

Esteso, A., Alemany, M. M., & Ortiz, A. (2018). Conceptual framework for designing agri-food supply chains under uncertainty by mathematical programming models. *International Journal of Production Research, 56*(13), 4418–4446.

Etemadnia, H., Goetz, S. J., Canning, P., & Tavallali, M. S. (2015). Optimal wholesale facilities location within the fruit and vegetables supply chain with bimodal transportation options: An LP-MIP heuristic approach. *European Journal of Operational Research, 244*(2), 648–661.

FAO. (2011). Global food losses and food waste—Extent, causes and prevention. Rome.

FAO, Ifad, UNICEF, WFP, & WHO. (2019). *The state of food security and nutrition in the world 2019. Safeguarding against economic slowdowns and downturns*. Rome: FAO.

Farahani, R. Z., SteadieSeifi, M., & Asgari, N. (2010). Multiple criteria facility location problems: A survey. *Applied Mathematical Modelling, 34*(7), 1689–1709.

Florentino, H. D. O., Cantane, D. R., Jones, D. F., Ouelhadj, D., Khosravi, B., & Irawan, C. A. (2020). An optimization model for combined selecting, planting and harvesting sugarcane varieties. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03610-y.

Food Corporation of India. Retrieved January 5, 2018, from http://fci.gov.in/movements.php?view=32.

Ge, H., Goetz, S., Canning, P., & Perez, A. (2018). Optimal locations of fresh produce aggregation facilities in the United States with scale economies. *International Journal of Production Economics, 197*(January), 143–157.

Ge, H., Gray, R., & Nolan, J. (2015). Agricultural supply chain optimization and complexity: A comparison of analytic vs simulated solutions and policies. *International Journal of Production Economics, 159,* 208–220.

Gholamian, M. R., & Taghanzadeh, A. H. (2017). Integrated network design of wheat supply chain: A real case of Iran. *Computers and Electronics in Agriculture, 140,* 139–147.

Göbel, C., Langen, N., Blumenthal, A., Teitscheid, P., & Ritter, G. (2015). Cutting food waste through cooperation along the food supply chain. *Sustainability, 7*(2), 1429–1445.

Govindan, K., Jafarian, A., Khodaverdi, R., & Devika, K. (2014). Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics, 152,* 9–28.

Gustavsson, J., Cederberg, C., Sonesson, U., Van Otterdijk, R., & Meybeck, A. (2011). Global food losses and food waste: Extent, causes and prevention, FAO, Rome, Italy. Retrieved August 12, 2018 from http://www.fao.org/docrep/014/mb060e/mb060e00.pdf.

Hamadani, A. Z., Abouei Ardakan, M., Rezvan, T., & Honarmandian, M. M. (2013). Location-allocation problem for intra-transportation system in a big company by using meta-heuristic algorithm. *Socio-Economic Planning Sciences, 47*(4), 309–317.

Hosseini-Motlagh, S. M., Samani, M. R. G., & Saadi, F. A. (2019). A novel hybrid approach for synchronized development of sustainability and resiliency in the wheat network. *Computers and Electronics in Agriculture, 168,* 105095.

Kaur, H. (2019). *Modelling internet of things driven sustainable food security system*. Benchmarking: An International Journal. https://doi.org/10.1108/BIJ-12-2018-0431.

Ketzenberg, M., Bloemhof, J., & Gaukler, G. (2015). Managing perishables with time and temperature history. *Production and Operations Management, 24*(1), 54–70.

Khalifehzadeh, S., Seifbarghy, M., & Naderi, B. (2015). A four-echelon supply chain network design with shortage: Mathematical modeling and solution methods. *Journal of Manufacturing Systems, 35,* 164–175.

Khamjan, W., Khamjan, S., & Pathumnakul, S. (2013). Determination of the locations and capacities of sugar cane loading stations in Thailand. *Computers & Industrial Engineering, 66*(4), 663–674.

Kiil, K., Dreyer, H. C., Hvolby, H. H., & Chabada, L. (2018). Sustainable food supply chains: The impact of automatic replenishment in grocery stores. *Production Planning & Control, 29*(2), 106–116.

Krishnan, R., Agarwal, R., Bajada, C., & Arshinder, K. (2020). Redesigning a food supply chain for environmental sustainability—An analysis of resource use and recovery. *Journal of Cleaner Production, 242,* 118374.

Leat, P., & Revoredo-Giha, C. (2013). Risk and resilience in agri-food supply chains: The case of the ASDA PorkLink supply chain in Scotland. *Supply Chain Management: An International Journal, 18*(2), 219–231.

Liotta, G., Stecca, G., & Kaihara, T. (2015). Optimisation of freight flows and sourcing in sustainable production and transportation networks. *International Journal of Production Economics, 164,* 351–365.

Maiyar, L. M., & Thakkar, J. J. (2017). A combined tactical and operational deterministic food grain transportation model: Particle swarm based optimization approach. *Computers & Industrial Engineering, 110,* 30–42.

Maiyar, L. M., & Thakkar, J. J. (2019). Modelling and analysis of intermodal food grain transportation under hub disruption towards sustainability. *International Journal of Production Economics*. https://doi.org/10.1016/J.IJPE.2018.07.021.

Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2009). Facility location and supply chain management—A review. *European Journal of Operational Research, 196,* 401–412.

Milman, O. (2015). Earth has lost a third of arable land in past 40 years, scientists say. Retrieved August 14, 2019, from https://www.theguardian.com/environment/2015/dec/02/arable-land-soil-food-security-shortage.

Mishra, N., & Singh, A. (2018). Use of twitter data for waste minimisation in beef supply chain. *Annals of Operations Research, 270*(1–2), 337–359.

Mogale, D. G., Cheikhrouhou, N., & Tiwari, M. K. (2019a). Modelling of sustainable food grain supply chain distribution system: A bi-objective approach. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2019.1669840.

Mogale, D. G., Ghadge, A., Kumar, S. K., & Tiwari, M. K. (2019b). Modelling supply chain network for procurement of food grains in India. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2019.1682707.

Mogale, D. G., Kumar, M., Kumar, S. K., & Tiwari, M. K. (2018a). Grain silo location-allocation problem with dwell time for optimization of food grain supply chain network. *Transportation Research Part E: Logistics and Transportation Review, 111,* 40–69.

Mogale, D. G., Kumar, S. K., Márquez, F. P. G., & Tiwari, M. K. (2017). Bulk wheat transportation and storage problem of public distribution system. *Computers & Industrial Engineering, 104,* 80–97.

Mogale, D. G., Kumar, S. K., & Tiwari, M. K. (2018b). An MINLP model to support the movement and storage decisions of the Indian food grain supply chain. *Control Engineering Practice, 70,* 98–113.

Mohammed, Ahmed, & Wang, Qian. (2017). The Fuzzy Multi-Objective Distribution Planner for a Green Meat Supply Chain. *International Journal of Production Economics, 184,* 47–58.

Naderi, B., Govindan, K., & Soleimani, H. (2019). A Benders decomposition approach for a real case supply chain network design with capacity acquisition and transporter planning: Wheat distribution network. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03137-x.

Nicholson, C. F., Gómez, M. I., & Gao, O. H. (2011). The costs of increased localization for a multiple-product food supply chain: Dairy in the United States. *Food Policy, 36*(2), 300–310.

Nourbakhsh, S. M., Bai, Y., Maia, G. D. N., Ouyang, Y., & Rodriguez, L. (2016). Grain supply chain network design and logistics planning for reducing post-harvest loss. *Biosystems Engineering, 151,* 105–115.

Orgut, I. S., Ivy, J., & Uzsoy, R. (2017). Modeling for the equitable and effective distribution of food donations under stochastic receiving capacities. *IISE Transactions, 49*(6), 567–578.

Orjuela-Castro, J. A., Sanabria-Coronado, L. A., & Peralta-Lozano, A. M. (2017). Coupling facility location models in the supply chain of perishable fruits. *Research in Transportation Business and Management, 24,* 73–80.

Paksoy, T., Pehlivan, N. Y., & Özceylan, E. (2012). Application of fuzzy optimization to a supply chain network design: A case study of an edible vegetable oils manufacturer. *Applied Mathematical Modelling, 36*(6), 2762–2776.

Parwez, S. (2014). Food supply chain management in Indian Agriculture: Issues, opportunities and further research. *African Journal of Business Management, 8*(14), 572–581.

Pongchairerks, P., & Kachitvichyanukul, V. (2009). Particle swarm optimization algorithm with multiple social learning structures. *International Journal of Operational Research, 6*(2), 176–194.

Ramanathan, V., S. Sundar, R. Harnish, S. Sharma, J. Seddon, B. Croes, A. Lloyd, et al. (2014). *India California air pollution mitigation program: Options to reduce road transport pollution in India*. Published by The Energy and Resources Institute in collaboration with the University of California at San Diego and the California Air Resources Board.

Rancourt, M. È., Cordeau, J. F., Laporte, G., & Watkins, B. (2015). Tactical network planning for food aid distribution in Kenya. *Computers & Operations Research, 56,* 68–83.

Raut, R. D., Gardas, B. B., Kharat, M., & Narkhede, B. (2018). Modeling the drivers of post-harvest losses–MCDM approach. *Computers and Electronics in Agriculture, 154,* 426–433.

Report of the Comptroller and Auditor General of India. (2013). *Storage management and movement of food grains in food corporation of India*. New Delhi: Union Government Ministry of Consumer Affairs, Food and Public Distribution.

ReVelle, C. S., & Eiselt, H. A. (2005). Location analysis: A synthesis and survey. *European Journal of Operational Research, 165*(1), 1–19.

Rohmer, S. U. K., Gerdessen, J. C., & Claassen, G. D. H. (2019). Sustainable supply chain design in the food system with dietary considerations: A multi-objective analysis. *European Journal of Operational Research, 273*(3), 1149–1164.

Sachan, A., Sahay, B. S., & Sharma, D. (2005). Developing Indian grain supply chain cost model: A system dynamics approach. *International Journal of Productivity and Performance Management, 54*(3), 187–205.

Sharon, M., Abirami, C. V., & Alagusundaram, K. (2014). Grain storage management in India. *Journal of Postharvest Technology, 2*(1), 12–24.

Sheane, R., McCosker, C., & Royston, S. (2018). Report of Food system framework: A focus on food sustainability.

Shukla, M., & Jharkharia, S. (2013). Agri-fresh produce supply chain management: A state-of-the-art literature review. *International Journal of Operations & Production Management, 33*(2), 114–158.

Soleimani, H., & Kannan, G. (2015). A hybrid particle swarm optimization and genetic algorithm for closed-loop supply chain network design in large-scale networks. *Applied Mathematical Modelling, 39*(14), 3990–4012.

Song, M., Wang, S., & Fisher, R. (2014). Transportation, iceberg costs and the adjustment of industrial structure in China. *Transportation Research Part D: Transport and Environment, 32,* 278–286.

Soto-Silva, W. E., Nadal-Roig, E., González-Araya, M. C., & Pla-Aragones, L. M. (2016). Operational research models applied to the fresh fruit supply chain. *European Journal of Operational Research, 251*(2), 345–355.

Soysal, M., Bloemhof-Ruwaard, J. M., & Van Der Vorst, J. G. A. J. (2014). Modelling food logistics networks with emission considerations: The case of an international beef supply chain. *International Journal of Production Economics, 152,* 57–70.

Timperley, J. (2019). The carbon brief profile: India. Retrieved August 14, 2019, from https://www.carbonbrief.org/the-carbon-brief-profile-india.

Validi, S., Bhattacharya, A., & Byrne, P. J. (2014). A case analysis of a sustainable food supply chain distribution system—A multi-objective approach. *International Journal of Production Economics, 152,* 71–87.

Validi, S., Bhattacharya, A., & Byrne, P. J. (2018). Sustainable distribution system design: A two-phase DoE-guided meta-heuristic solution approach for a three-echelon bi-objective AHP-integrated location-routing model. *Annals of Operations Research*. https://doi.org/10.1007/s10479-018-2887-y.

Veeramachaneni, K., Peram, T., Mohan, C., & Osadciw, L. A. (2003). Optimization using particle swarms with near neighbor interactions. In *Genetic and evolutionary computation conference* (pp. 110–121). Springer, Berlin.

Vlajic, J. V., Van der Vorst, J. G., & Haijema, R. (2012). A framework for designing robust food supply chains. *International Journal of Production Economics, 137*(1), 176–189.

Wang, F., Lai, X., & Shi, N. (2011). A multi-objective optimization for green supply chain network design. *Decision Support Systems, 51*(2), 262–269.

Wang, X., Li, D., & Shi, X. (2012). A fuzzy model for aggregative food safety risk assessment in food supply chains. *Production Planning & Control, 23*(5), 377–395.

Wisittipanich, W., & Hengmeechai, P. (2017). Truck scheduling in multi-door cross docking terminal by modified particle swarm optimization. *Computers & Industrial Engineering, 113,* 793–802.

Xu, J., Yan, F., & Li, S. (2011). Vehicle routing optimization with soft time windows in a fuzzy random environment. *Transportation Research Part E: Logistics and Transportation Review, 47*(6), 1075–1091.

Yakavenka, V., Mallidis, I., Vlachos, D., Iakovou, E., & Eleni, Z. (2019). Development of a multi-objective model for the design of sustainable supply chains: The case of perishable food products. *Annals of Operations Research.* https://doi.org/10.1007/s10479-019-03434-5.

Yamada, T., & Febri, Z. (2015). Freight transport network design using particle swarm optimisation in supply chain-transport supernetwork equilibrium. *Transportation Research Part E: Logistics and Transportation Review, 75,* 164–187.

Zhao, X., & Dou, J. (2011). A hybrid particle swarm optimization approach for design of agri-food supply chain network. In *2011 IEEE international conference on service operations, logistics, and informatics (SOLI)* (pp. 162–167).

Zhu, Z., Chu, F., Dolgui, A., Chu, C., Zhou, W., & Piramuthu, S. (2018). Recent advances and opportunities in sustainable food supply chain: A model-oriented review. *International Journal of Production Research, 56*(17), 5700–5722.

Zhu, Y., Ge, H., & Zhen, T. (2009). Hybrid particle swarm algorithm for grain logistics vehicle routing problem. In *3rd International symposium on intelligent information technology application, IITA 2009*, (Vol. 2, pp. 364–367).