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# Optimizing perishable food products across states: A multi objective evolutionary algorithm for surplus to deficit transportation

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ABSTRACT

Ensuring the seamless flow of goods from farmer to stakeholder is paramount especially considering the facts such as demand fluctuations, quantity availability, vehicle capacity, inventory limits and truck preferences. In this paper, we proposed a mixed integer linear programming (MILP) model for distributing perishable food goods from surplus states to surplus and deficit state wholesalers in the Indian subcontinent, with the goal of minimizing total cost (fixed, variable, and operational) and transportation time. To ensure product delivery on time, we looked at various scenarios including a case with real-life constraints. Solving this computationally complex task with conflicting objectives in a reasonable time is difficult. To handle the aforementioned multi-objective problem, we proposed an evolutionary algorithm based modified non-dominated sorting genetic algorithm II (MNSGA-II). Furthermore, the suggested algorithm's performance is tested against the most extensively used multi-objective algorithm, Non-dominated Sorting Genetic method-II (NSGA-II). According to the findings, the proposed MNSGA-II outperforms practically all instances.

## 1. Introduction

India is the world's second-largest producer of food grains, boasting significant crop yields like tomatoes and wheat (Jhajharia and Mathur, 2023; Seth et al., 2023). Tomato production, a vital agricultural activity in India, contributes to 10% of global output, with yields averaging 35 tons per hectare and hybrid varieties reaching up to 50 tons per hectare (Statista, 2023). Despite this agricultural prowess, India grapples with providing safe, nutritious, and high-quality food to its population exceeding one billion (DeFries et al., 2023). A primary concern in the food supply chain (SC) is the waste. As the food products are perishable in nature, the SC is termed as Perishable Food Supply Chain (PFSC) where food items have a limited shelf life, and improper handling during transportation of these freshly harvested products from farms to consumers leads to spoilage. This necessitates efficient inventory routing strategies to transport Perishable Food Products (PFP) to consumers. According to an estimation by Food and Agricultural Organization of the United Nations (FAO), about one-third of global food production is wasted annually. PFSCs account for a significant portion of this waste (FAO, 2019), highlighting the urgent need for effective perishable inventory routing practices. Furthermore, effective PFSC management necessitates collaborative efforts among SC stakeholders such as farmers, mandis, and wholesalers. This collaboration is pivotal for enhancing communication, reducing waste, and ensuring food safe, cost-effective, and timely delivery to consumers (Broekmeulen and van Donselaar, 2019).

The Perishable Inventory Routing Problem (PIRP) presents a complex logistical challenge, integrating inventory management and vehicle routing decisions for perishable products (Shaabani, 2022). It is essentially a variant of the Inventory Routing Problem (IRP), which involves optimizing transportation and inventory decisions to ensure timely delivery of the right amount of goods while minimizing costs and time (Bell et al., 1983; Coelho et al., 2014; Moin and Salhi, 2007). Initially inspired by the perishable nature of human blood in healthcare applications (Federgruen et al., 1986; Le et al., 2013), PIRP extends to fresh produce agri-food supply chains.

Several methods have been proposed to address the PIRP. Onggo et al. (2019) introduced a mixed integer program (MIP) and a simheuristic algorithm that combines metaheuristics with Monte Carlo simulation. Yantong et al. (2016) presented a new model for the

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Inventory Routing Problem (IRP), which simultaneously considers economic, customer satisfaction, and green criteria. Other approaches include MILP solvers proposed by Amorim et al. (2012); Rahimi et al. (2014 & 2015), Genetic algorithms utilized by Azadeh et al. (2017), Hiassat et al. (2017), and Yavari et al. (2020), NSGA-II as employed by Rahimi et al. (2017) and Tavana et al. (2018), Variable Neighborhood Search by Popović et al. (2012), and Particle Swarm Optimization by Widyadana and Irohara (2019).

Although several studies, PIRP presents unique challenges due to the perishable nature of its products, adding complexity beyond conventional IRP. While less frequent deliveries reduce routing costs, they also increase the risk of product deterioration or waste due to perishability. Balancing routing costs and delivery times is crucial in PIRP. One effective strategy involves PFPs with shorter shelf lives to nearby consumers, and those with longer shelf lives to distant consumers. This strategy considers regional production capacity relative to demand, with some regions classified as surplus and others as deficit. Surplus states boast production capacities exceeding demand levels while deficit states experience demand levels surpassing production capacities. PFPs with shorter shelf lives should be directed to nearby surplus regions, while those with longer shelf lives should be routed to distant deficit regions. Surprisingly, there needs to be more attention to this aspect of PIRP, particularly the movement of PFP from surplus to deficit regions based on their shelf life, while ensuring optimal inventory routing.

Hence, this study aims to address several key aspects within the PIRP scope. This includes identifying surplus and deficit states of PFP, incorporating realistic constraints such as truck capacity, preference, inventory capacity, availability, and demand constraints, and devising efficient distribution strategies for PFP. Furthermore, as critical factors such as optimal total cost (TC), transportation time (TT), inventory routing, and perishable shelf life are still need to be studied in the context of PIRP, we fill this gap within the Indian context by exploring multiple scenarios for optimizing TC and TT across different configurations. A primary challenge this study highlights is the effective distribution of agricultural commodities throughout the SC. Optimizing operations at every level is essential to ensure the timely delivery of fresh supplies while minimizing costs. In this regard, the following research questions are addressed.

- How can the distribution of PFP be optimized effectively from surplus to deficit and surplus state wholesalers?
- What practical constraints need to be considered in developing a MILP mathematical model for optimizing the distribution of PFP?
- How can the proposed approach simultaneously optimize TC and TT in the distribution of bulk PFP from surplus to deficit and surplus wholesalers?

The following are the main contributions of this paper:

1. A multi-objective MILP model has been proposed to address perishable inventory routing, considering factors such as perishability and vehicle capacity. This model aims to optimize the transportation and inventory management of PFP while balancing *multiple conflicting objectives*, such as minimizing costs and minimizing time.
2. We build the *potential commodity's SC configuration* by collecting data and analysing the PFSC dynamics, optimizing inventory routing, and ensuring sustainability.
3. A *Modified Non-dominated Sorting Genetic Algorithm- II (MNSGA-II)* method has been proposed to find a near optimal solution to the conflicting objectives.

The sections of the paper are organized as follows: Section 2 summarizes previous research on the PFSC issues and its solution methodologies, emphasizing key findings and identifying gaps. Section 3 outlines the problem description and the construction of the mathematical model. The steps involved in the proposed meta-heuristic algorithm are described in Section 4. Section 5 discusses the computational outcomes of various experimental situations on the goals under consideration. Section 6 discusses the study's findings.

## 2. Literature review

Managing the PFSC is a difficult and intricate task, including overseeing transportation, inventory routing, and timely delivery of high PFP. In recent years, PFSC optimization has been a research topic, with the goal of ensuring that food items arrive at their destination in good condition and within their shelf life. The research aims to optimize TC and TT by addressing the PIRP from multiple perspectives. Various enablers, such as shelf life, transportation cost, operational cost, inventory control, vehicle routing, and decision-making, are considered when transporting PFP from surplus to deficit states. This review of the literature looks at recent research on PFP enablers and PFSC optimization techniques.

### 2.1. Perishable food supply chain (PFSC) enablers

Interest in managing PFSC has sparked numerous studies aiming to boost efficiency and highlight the importance of effective management (Bogataj et al., 2005; Mohan et al., 2013). PFSCs pose complex challenges, including fluctuating demands, environmental limitations, and disruptions. Researchers have delved into understanding the key drivers, critical factors, and sustainable practices within PFSCs to address these hurdles. Balaji and Arshinder (2016) conducted an insightful review of PFSCs using innovative techniques, shedding light on the unique complexities of managing PFP in the supply chain.

Recent studies highlight the imperative of enhancing efficiency, sustainability, and resilience within PFSCs. Chauhan et al. (2020) delves into the complexities of managing perishable goods and stresses the significance of resilience and flexibility, especially in preparing for pandemics. They advocate for strategies such as flexibility, market research, and stakeholder collaboration to bolster SC preparedness. Concurrently, attention is drawn towards sustainability, environmental impact, and economic concerns (Soysal et al., 2015; Chen et al., 2022; Kazemi et al., 2017; Shaabani and Kamalabadi, 2016). Factors like global warming, carbon emissions, and the use of eco-friendly packaging materials emerge as crucial elements for ensuring the long-term viability of fresh food SCs (Sharma et al., 2023). Despite the scarcity of research on the PIRP, various variants have been proposed. Batero-Manso and Orjuela-Castro (2018) conduct a comprehensive analysis of these variations, encompassing aspects such as multiple-product scenarios, transshipments, facility location decisions, and sustainability issues. Additionally, Birkmaier et al. (2024) shed light on the potential of data-driven forecasting methods to minimize waste in PFSCs, offering valuable insights into optimizing SC planning for perishable foods.

Furthermore, transportation is a critical aspect of PFSCs. Efficient transportation is pivotal in ensuring the timely delivery of perishable goods, minimizing spoilage, and optimizing SC operations. Cantu-Funes et al. (2018) developed a MILP mathematical model to optimize the objective for a multi-depot periodic vehicle routing problem with time windows using a heuristic algorithm. Shi et al. (2023) devised a large neighborhood search-based adaptive technique to solving a vehicle routing problem with zone-based pricing in order to optimize profit. Karanam et al. (2022a) investigated the factors facilitating PFSC movement in the SC from source to destination. Their research utilized TISM-MICMAC analysis and VOSviewer keyword co-occurrence analysis to explain the PFSC enabler hierarchy thoroughly. Subsequent studies by Karanam et al. (2022b) further explored PFSC enablers using DEMATEL and AHP-PROMETHEE techniques, revealing critical factors, including operation and transportation costs, shelf life, inventory routing, and decision-making. Our study considers various enablers, such as shelf life, transportation cost, operational cost, inventory control, vehicle routing, and decision-making when transporting perishable food products from

surplus to deficit states.

### 2.2. Perishable food supply chain models and approaches

Perishable food supply chain (PFSC) models address the challenges in transporting, storing, and distributing perishable goods. The main objectives of these models are to optimize inventory management, delivery times, and freshness while minimizing waste. Regarding inventory control strategies, Gutierrez-Alcoba et al. (2017) developed a simple heuristic for managing perishable item inventory. Similarly, Ngoc and Nananukul (2017) proposed aggregation techniques to enhance inventory and production decisions. Focusing on optimization, Wang et al. (2018, 2021) explored cost-effective distribution and collaborative approaches to designing fresh logistics distribution networks. Wang et al. (2020) further optimized green logistics location routing operations by considering time windows. More recent studies by Hamid et al. (2023) and Taheri and Taft (2024) aimed at reducing transportation costs and improving reliability through multi-objective optimization and hybrid approaches. Wang et al. (2023) introduced a two-echelon multi-depot multi-period location-routing problem with pickup and delivery considerations. Building on this, Wang et al. (2024) proposed a multi-depot vehicle routing problem that incorporates intelligent recycling prices, emphasizing environmental regulations and the economic benefits of recycling.

Perishable food supply chains pose complex optimization challenges due to NP-hard problems, conflicting objectives, and intricate variables like product quality deterioration and demand uncertainty. To tackle these challenges, researchers and practitioners frequently resort to heuristics and meta-heuristics for their efficiency in navigating complex problem spaces and finding near-optimal solutions within reasonable timeframes (Hauser and Chung, 2006; Borisovsky et al., 2009; Bachlaus et al., 2009; Pal et al., 2011; Essafi et al., 2012; Taleizadeh et al., 2013; González et al., 2022; Detwal et al., 2023; Pérez et al., 2023; Przewozniczek et al., 2020; Shi et al., 2023; Khalili-Fard et al., 2024).

In inventory optimization, Taleizadeh et al. (2008a) introduced a search algorithm for solving the integer-nonlinear problem and employed a simulation annealing approach for multi-product, multi--constraint inventory control systems. They developed an EOQ model for ordering raw materials, utilizing a hybrid harmony search algorithm (Taleizadeh et al., 2008b). Subsequently, addressing the newsstand problem with two objectives, they introduced a hybrid method of goal programming and a genetic algorithm (Taleizadeh et al., 2009). To account for stochasticity in inventory control problems, Taleizadeh et al. (2010) developed a fuzzy mixed integer non-linear programming model, solved using a hybrid meta-heuristic intelligent algorithm. Considering various costs such as transportation, fixed, holding, and clearance costs for optimizing multi-product inventory control problems, they utilized an uncertain programming genetic algorithm (Taleizadeh et al., 2011).

Within the context of PFP, Wang et al. (2021) utilized tabu search NSGA-II to optimize the objectives in a collaborative approach for designing and managing fresh logistics distribution networks. Similarly, Tirkolaee et al. (2020) employed NSGA-II and simulated annealing to develop a multi-objective mathematical model to minimize pollution in the transportation process, offering a practical solution for optimizing transportation networks while considering environmental sustainability. Kumar et al. (2022) applied a differential evolutionary algorithm as a meta-heuristic approach for perishable product inventory routing in another study.

Addressing challenges in transporting, storing, and distributing perishable goods, PFSC models strive to optimize inventory management, delivery times, and freshness while minimizing waste, Ahumada and Villalobos (2011a, 2011b) explored integrated tactical models and operational planning for distributing and producing agricultural products. Mogale et al. (2017a) focused on minimizing handling, storage, and transportation costs in the two-stage food grain transportation problem, later optimizing total transportation costs using the Max-Min Ant System (Mogale et al., 2017b). Introducing flexibility into transportation, Maiyar and Thakkar (2020) addressed the Indian food grain supply chain. Yantong et al. (2016) proposed a model to maximize profits while maintaining food quality standards in perishable inventory routing. Daneshvar et al. (2023) tackled the challenge of optimizing the distribution of agricultural and highly perishable items under uncertainty, utilizing genetic, whale, and mathematical optimization techniques.

Ghasemi et al. (2022) developed a bi-level MILP model for the blood supply chain network under uncertainty, employing the Stackelberg game theory technique to maximize donor utility and minimize total cost. Similarly, Ghasemi et al. (2023) devised a multi-objective mathematical model for the plasma supply chain network under uncertainty, aiming to maximize blood donors' coverage and minimize transportation costs using the ε-constraint method and multi-objective invasive weed optimization. These studies collectively offer valuable insights into how optimization models and methodologies can enhance perishable food supply chain management, encouraging further exploration into metaheuristic methods for solution optimization, such as MNSGA-II and NSGA-II.

### 2.3. Literature summary and research gap

The literature review provides a comprehensive overview of research efforts in PFSCs. It highlights the complexity of PFSCs, including fluctuating demands, and environmental constraints. Researchers have investigated key drivers, critical factors, and sustainable practices within PFSCs to address these challenges. Additionally, the review discusses various optimization models and methodologies employed to enhance PFSC management, including heuristics and meta-heuristics. Despite the significant advancements in understanding and optimizing PFSCs, several research gaps still need to be addressed. While transportation is acknowledged as a critical aspect, there is a need for further exploration into advanced transportation optimization techniques explicitly tailored to the unique challenges of PFSCs. To optimize the inventory routing of PFPs in the perishable food supply chain, only some researchers explored the problem, while still gap exists for managing inventory among surplus and deficit regions. Addressing these research gaps will contribute to developing more robust PFSC solutions.

## 3. Problem statement and mathematical model

The problem statement and mathematical formulation of the PIRP's multi-objective MILP model in the context of PFSC are described in this section.

### 3.1. Problem description

India's vast population, currently at 1.37 billion according to the United Nations Department of Economic and Social Affairs: Population Division, World Population Prospects: The 2019 Revision, places immense strain on its natural resources. This strain manifests in various forms, including limited availability and deteriorating quality of soils, water, air, and forests. Climate change exacerbates these challenges, with rising temperatures, droughts in western and southern India, and floods in northern regions. The increasing pressure on natural resources directly impacts India's food supply chain (FSC), particularly concerning fruits and vegetables, essential components of the Indian diet. As urbanization and population growth continue, the demand for safe and healthy food rises. However, the distribution of perishable goods needs to be more efficient, characterized by high intermediation costs and post-harvest food losses. To address these challenges, this paper focuses on distributing perishable food products (PFP) from surplus state farmers to wholesalers across both surplus and deficit states within India. This necessitates the consideration of a three-echelon supply chain comprising farmers, mandis, and wholesalers.

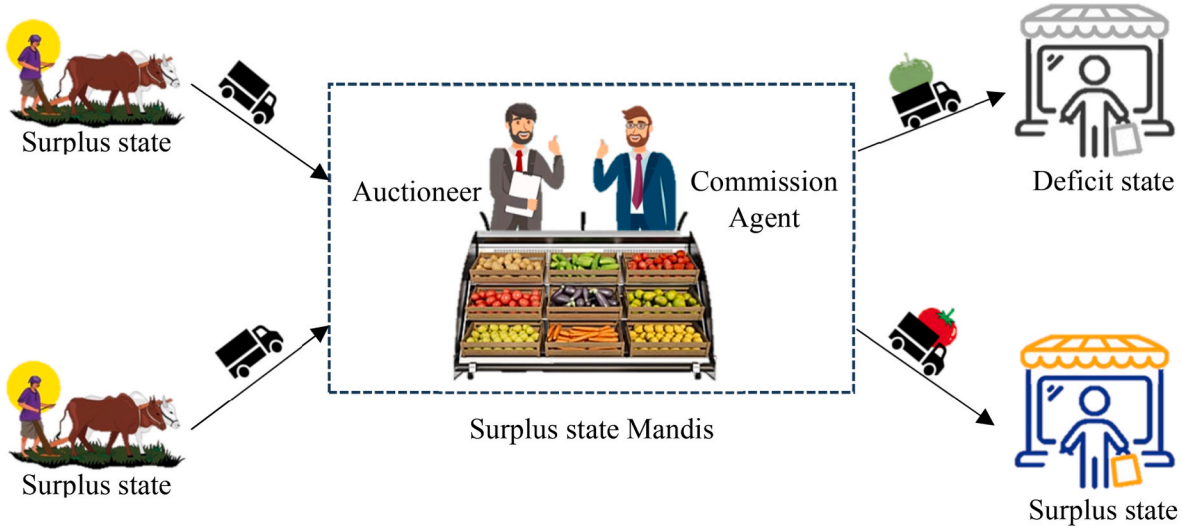



**Fig. 1.** Flow of products from farmer to wholesaler in the PFSC.

Tomatoes, a staple in the Indian diet, are chosen as the perishable agricultural product for analysis. Their limited shelf life and alignment with the end of the Rabi season and the onset of the monsoon (spanning from November to May) make them an ideal candidate for examining distribution challenges. Major tomato-producing and consuming states such as Andhra Pradesh, Karnataka, Tamil Nadu, Kerala, and Odisha are integral to the analysis.

The supply chain begins with private agencies purchasing farmers' harvests from various centres at a minimum support price. Trucks transport these harvested items to the mandis, where auctioneers and commission agents negotiate starting and reserve prices. At this stage, tomatoes are sorted based on their freshness, with green ones directed to deficit state wholesalers through the surplus state mandi, while red tomatoes follow the same route to surplus states. Given the shorter shelf life of red tomatoes due to quicker ripening and decay, they are prioritized for faster transportation. Once the auction concludes, wholesalers distribute the tomatoes to various channels, including cart sellers, shops, and supermarkets, at the auctioned price. Finally, consumers access these tomatoes through small businesses, completing the supply chain cycle at depicted in Fig. 1.

The research aims to optimize the transportation of bulk PFP and the number of intermediaries mandis and wholesalers in both deficit and surplus states, aiming to reduce TC and TT. Factors like truck capacity, freight cost per kilometer, and the availability of surplus and deficit trucks influence transportation costs. A limited number of vehicles with varying capacities and road transportation modes are considered. The study's framework comprises three stages: problem definition and objective setting, MILP mathematical model development, and selection of metaheuristic algorithms for evaluation and optimization. Finally, the most effective metaheuristic algorithm is chosen based on comparative analysis.

### 3.2. Mathematical model

In this section, a MILP model was developed to depict the PIRP. The objective is to minimize the TC and TT by adjusting the transfer amount and route for different nodes across various scenarios. To facilitate this, several assumptions were made, which are outlined as follows:

**Assumption 1.** Demand is predictable and deterministic in both surplus and deficit states.

Assumption 1 is considered to avoid stochasticity. Demand is predictable and deterministic because it is influenced by a variety of factors that can be measured and analyzed. These factors include consumer income, preferences, and willingness to substitute one product for another, as well as market penetration and the marginal utility of goods. In the context of surplus and deficit states, demand is influenced by the price of a product or resource, which is determined by the intersection of supply and demand curves (Li et al., 2021).

**Assumption 2.** Each mandi and wholesaler has a limited number of trucks with varying capacities available during each time period. Here, three types of trucks with varying capacities are used on all routes.

Assuming limited truck availability with varying capacities is crucial for efficient logistics management, enabling optimal resource allocation and route planning to minimize costs and maximize utilization. This assumption ensures realistic modeling, facilitating effective transportation operations for mandis and wholesalers.

**Assumption 3.** The variable transportation cost is dependent on the quantity to be shipped and the distance between nodes.

Assumption 3 recognizes the dual influence of shipment quantity and distance on transportation costs, challenging traditional cost models.

**Assumption 4.** This study focuses on ensuring farmers' total output sufficiently meets the demand of both surplus and deficit state wholesalers, without considering shortages in the analysis.

Assumption 4 is considered to balance the supply and demand of agricultural products in both surplus and deficit states, ensuring that farmers produce enough to meet the needs of wholesalers in both types of regions.

The following (Table 1) are the notations used throughout this paper.

Objective Functions

$$
\begin{aligned}
Min\,TC = \Bigg\{ & \sum_{f=1}^{F}\sum_{m=1}^{M}\sum_{h=1}^{H}\sum_{t=1}^{T}\left[\left(C_s^l N_{fm}^{lt}\right)+\left(P^l d_{fm} n_{fm}\right)\right] V_{fm}^t \\
& +\sum_{m=1}^{M}\sum_{w_s=1}^{W_s}\sum_{h=1}^{H}\sum_{t=1}^{T}\left[\left(C_s^l N_{mw_s}^{lt}\right)+\left(P^h d_{mw_s} n_{mw_s}\right)\varphi^t\right] Y_{mw_s}^t \\
& +\sum_{m=1}^{M}\sum_{w_d=1}^{W_d}\sum_{h=1}^{H}\sum_{t=1}^{T}\left[\left(C_d^l N_{mw_d}^{lt}\right)+\left(P^h d_{mw_d} n_{mw_d}\right)\lambda^t\right] X_{mw_d}^t \\
& +\sum_{t=1}^{T}\left[\sum_{f=1}^{F}\sum_{m=1}^{M}\left(n_{fm}B_m\right)+\sum_{m=1}^{M}\sum_{w_d=1}^{W_d}\left(n_{mw_d}B_{w_d}\right)+\sum_{m=1}^{M}\sum_{w_s=1}^{W_s}\left(n_{mw_s}B_{w_s}\right)\right]
\end{aligned}
\tag{1}
$$

**Table 1**
Notations.

| Indices | Description |
|---|---|
| $f = \{1,\ldots,F\}$ | Set of farmers |
| $m = \{1,\ldots,M\}$ | Set of mandis |
| $w_s = \{1,\ldots, W_s\}$ | Set of surplus state wholesalers |
| $w_d = \{1,\ldots, W_d\}$ | Set of deficit state wholesalers |
| $l = \{1,\ldots,L\}$ | Set of trucks |
| $t = \{1,\ldots,T\}$ | Set of time periods |
| *Vehicle related parameters* | |
| $\alpha^l$ | Capacity of truck of type $l$, where $l \in L$ |
| $N_{fm}^{lt}$ | Number of trucks used from farmer $f$ to mandi $m$ of type $l$ at time period $t$ |
| $N_{mw_s}^{lt}$ | Number of trucks used from mandi $m$ to surplus state wholesaler $w_s$ of type $l$ at $t$ |
| $N_{mw_d}^{lt}$ | Number of trucks used from $m$ to deficit state wholesaler $w_d$ of type $l$ at $t$ |
| $S_m^{lt}$ | Maximum number of trucks available at mandi $m$ |
| $S_{w_d}^{lt}$ | Maximum number of trucks available at deficit state wholesaler $w_d$ |
| $S_{w_s}^{lt}$ | Maximum number of trucks available at surplus state wholesaler $w_s$ |
| $A$ | Average speed of the vehicle |
| *Parameters of Distance and cost* | |
| $P^l$ | Unit freight cost of per Km per quantity tomatoes of truck of type $l$, where $l \in L$ |
| $d_{fm}$ | Distance in km from farmer $f$ to mandi $m$ |
| $d_{mw_d}$ | Distance in km from mandi $m$ to deficit state wholesaler $w_d$ |
| $d_{mw_s}$ | Distance in km from mandi $m$ to surplus state wholesaler $w_s$ |
| $C_s^l$ | Fixed transport cost of surplus state for a truck of type $l$ |
| $C_d^l$ | Fixed transport cost of deficit state for a truck of type $l$ |
| $B_m$ | Operational cost at mandi $m$ per unit quantity of tomato |
| $B_{w_d}$ | Operational cost at $w_d$ per unit quantity of tomato |
| $B_{w_s}$ | Operational cost at $w_s$ per unit quantity of tomato |
| *Quantity, capacity, and demand parameters* | |
| $Q_f^t$ | Quantity of tomato at farmer $f$ at any given time $t$ |
| $K_m^t$ | Quantity available at mandi $m$ at any given time $t$ |
| $n_{fm}$ | Quantity of tomatoes shipped from farmer $f$ to mandi $m$. |
| $n_{mw_d}$ | Quantity of tomatoes shipped from $m$ to deficit state wholesaler $w_d$. |
| $n_{mw_s}$ | Quantity of tomatoes shipped from $m$ to surplus state wholesaler $w_s$. |
| $D_{w_d}$ | Demand at deficit state wholesaler |
| $D_{w_s}$ | Demand at surplus state wholesaler |
| *Decision variables: Binary variables* | |
| $V_{fm}^t$ | 1 if farmer $f$ transports tomato to mandi $m$ in period $t$; otherwise, 0 |
| $X_{mw_d}^t$ | 1 if mandi $m$ transports tomato to deficit wholesaler $w_d$ in period $t$; otherwise, 0 |
| $Y_{mw_s}^t$ | 1 if mandi $m$ transports tomato to surplus wholesaler $w_s$ in period $t$; otherwise, 0 |
| $Z_{w_d}^{tl}$ | 1 if all trucks are full for deficit state $w_d$ at mandi $m$ in period $t$; otherwise, 0 |
| $Z_{w_s}^{tl}$ | 1 if all trucks are full for surplus state $w_s$ at mandi $m$ in period $t$; otherwise, 0 |
| $\lambda^t$ | 1 if color of tomato is greenish in time period $t$; otherwise, 0 |
| $\varphi^t$ | 1 if tomato is red in time period $t$; otherwise, 0 |

$$Min\ TT = {}^1\!/_A \sum_{l=1}^{L}\sum_{t=1}^{T}\left[N_{fm}^{lt}dt_{fm} + N_{mw_s}^{lt}d_{mw_s} + N_{mw_d}^{lt}d_{mw_d}\right] \tag{2}$$

Subject to constraints are:

$$\sum_{m=1}^{M} n_{fm}V_{fm}^t \le Q_f^t \quad \forall f \in F, \forall t \in T \tag{3}$$

$$\sum_{w_d}^{w_d}\left[n_{mw_d}X_{mw_d}^t\right] + \sum_{w_s=1}^{w_s}\left[n_{mw_s}Y_{mw_s}^t\right] \le K_m^t \quad \forall m \in M, \forall t \in T \tag{4}$$

$$\sum_{m=1}^{M}\sum_{w_d=1}^{w_d}\left[n_{mw_d}X_{mw_d}^t\right] \ge D_{w_d}^t \quad \forall w_d \in W_d, \forall t \in T \tag{5}$$

$$\sum_{m=1}^{M}\sum_{w_s=1}^{W_s}\left[n_{mw_s}Y_{mw_s}^t\right] \ge D_{w_s}^t \quad \forall w_s \in W_s, \forall t \in T \tag{6}$$

$$K_m^{t-1} + \sum_{f=1}^{F} n_{fm} - \sum_{w_s=1}^{W_s}\left[n_{mw_s}Y_{mw_s}^t\right] - \sum_{w_d=1}^{w_d}\left[n_{mw_d}X_{mw_d}^t\right] = K_m^t \quad \forall m \in M, \forall t \in T \tag{7}$$

$$K_m^{t=0} = 0 \quad \forall m \in M, \forall t \in T \tag{8}$$

$$n_{fm}V_{fm}^t \le \sum_{l=1}^{L} N_{fm}^{lt}\alpha^l \quad \forall f \in F, \forall m \in M, \forall t \in T \tag{9}$$

$$n_{mw_s}Y_{mw_s}^t \le \sum_{l=1}^{L} N_{mw_s}^{lt}\alpha^l \quad \forall w_s \in W_s, \forall m \in M, \forall t \in T \tag{10}$$

$$n_{mw_d}X_{mw_d}^t \le \sum_{l=1}^{L} N_{mw_d}^{lt}\alpha^l \quad \forall w_d \in W_d, \forall m \in M, \forall t \in T \tag{11}$$

$$\sum_{m=1}^{M} N_{fm}^{lt} \le S_m^{lt} \quad \forall f \in F, \forall l \in L, \forall t \in T \tag{12}$$

$$\sum_{w_s=1}^{W_s} N_{mw_s}^{lt} \le S_{w_s}^{lt} \quad \forall f \in F, \forall l \in L, \forall t \in T \tag{13}$$

$$\sum_{w_d=1}^{W_d} N_{mw_d}^{lt} \le S_{w_d}^{lt} \quad \forall f \in F, \forall l \in L, \forall t \in T \tag{14}$$

$$Z_{w_s}^{tl_1} \ge Z_{w_s}^{tl_2} \ge Z_{w_s}^{tl_3} \quad \forall w_s \in W_s, \forall l \in L, \forall t \in T \tag{15}$$

$$Z_{w_s}^{tl_1}S_{w_s}^{tl_1} \le \sum_{w_s=1}^{W_s} N_{mw_s}^{tl_1} \le S_{w_s}^{tl_1} \quad \forall w_s \in W_s, \forall l \in L, \forall t \in T \tag{16}$$

$$Z_{w_s}^{tl_2}S_{w_s}^{tl_2} \le \sum_{w_s=1}^{W_s} N_{mw_s}^{tl_2} \le S_{w_s}^{tl_2}\,Z_{w_s}^{tl_1} \quad \forall w_s \in W_s, \forall l \in L, \forall t \in T \tag{17}$$

$$Z_{w_s}^{tl_3}S_{w_s}^{tl_3} \le \sum_{w_s=1}^{W_s} N_{mw_s}^{tl_3} \le S_{w_s}^{tl_3}\,Z_{w_s}^{tl_2} \quad \forall w_s \in W_s, \forall l \in L, \forall t \in T \tag{18}$$

$$Z_{w_d}^{tl_1} \ge Z_{w_d}^{tl_2} \ge Z_{w_d}^{tl_3} \quad \forall w_d \in W_d, \forall l \in L, \forall t \in T \tag{19}$$

$$Z_{w_d}^{tl_1}S_{w_d}^{tl_1} \le \sum_{w_d=1}^{W_d} N_{mw_d}^{tl_1} \le S_{w_d}^{tl_1} \quad \forall w_d \in W_d, \forall l \in L, \forall t \in T \tag{20}$$

$$Z_{w_d}^{tl_2}S_{w_d}^{tl_2} \le \sum_{w_d=1}^{W_d} N_{mw_d}^{tl_2} \le S_{w_d}^{tl_2}\,Z_{w_d}^{tl_1} \quad \forall w_d \in W_d, \forall l \in L, \forall t \in T \tag{21}$$

$$Z_{w_d}^{tl_3}S_{w_d}^{tl_3} \le \sum_{w_d=1}^{W_d} N_{mw_d}^{tl_3} \le S_{w_d}^{tl_3}\,Z_{w_d}^{tl_2} \quad \forall w_d \in W_d, \forall l \in L, \forall t \in T \tag{22}$$

Domain Constraints

$$V_{fm}^t, Y_{mw_s}^t, X_{mw_d}^t, \varphi^t, \lambda^t, Z_m^{tl}, Z_{w_s}^{tl}, Z_{w_d}^{tl} = \{0,1\} \quad \forall f \in F, m \in M, w_s \in W_s, w_d \in W_d \tag{23}$$

$$N_{fm}^{lt}, N_{mw_s}^{lt}, N_{mw_d}^{lt}, n_{fm}, n_{mw_s}, n_{mw_d} \ge 0 \tag{24}$$

$$N_{fm}^{lt}, N_{mw_s}^{lt}, N_{mw_d}^{lt} \in Z \tag{25}$$

The first objective function (1) computes the TC of road

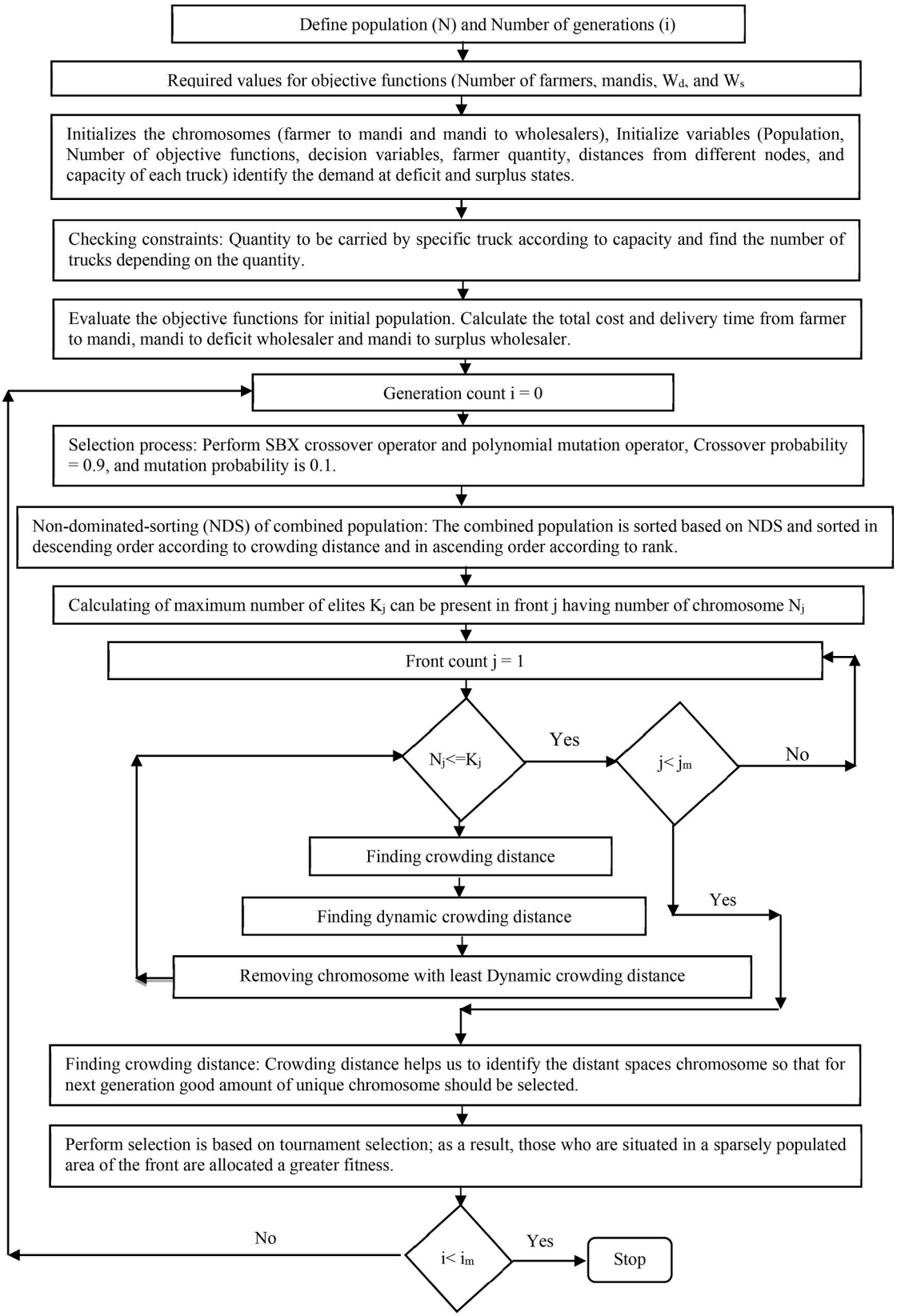



**Fig. 2.** The procedure for the proposed MNSGA-II.

6. Repeat the procedure until all wholesalers meet the availability constraint set by the mandi.
7. Concatenate all decision variables into a single array. The arrays of variables from farmer to mandi and from mandi to wholesaler are combined to form a single chromosome, and the values of two objective functions are evaluated and stored in the last and second last arrays, as shown in Fig. 5.

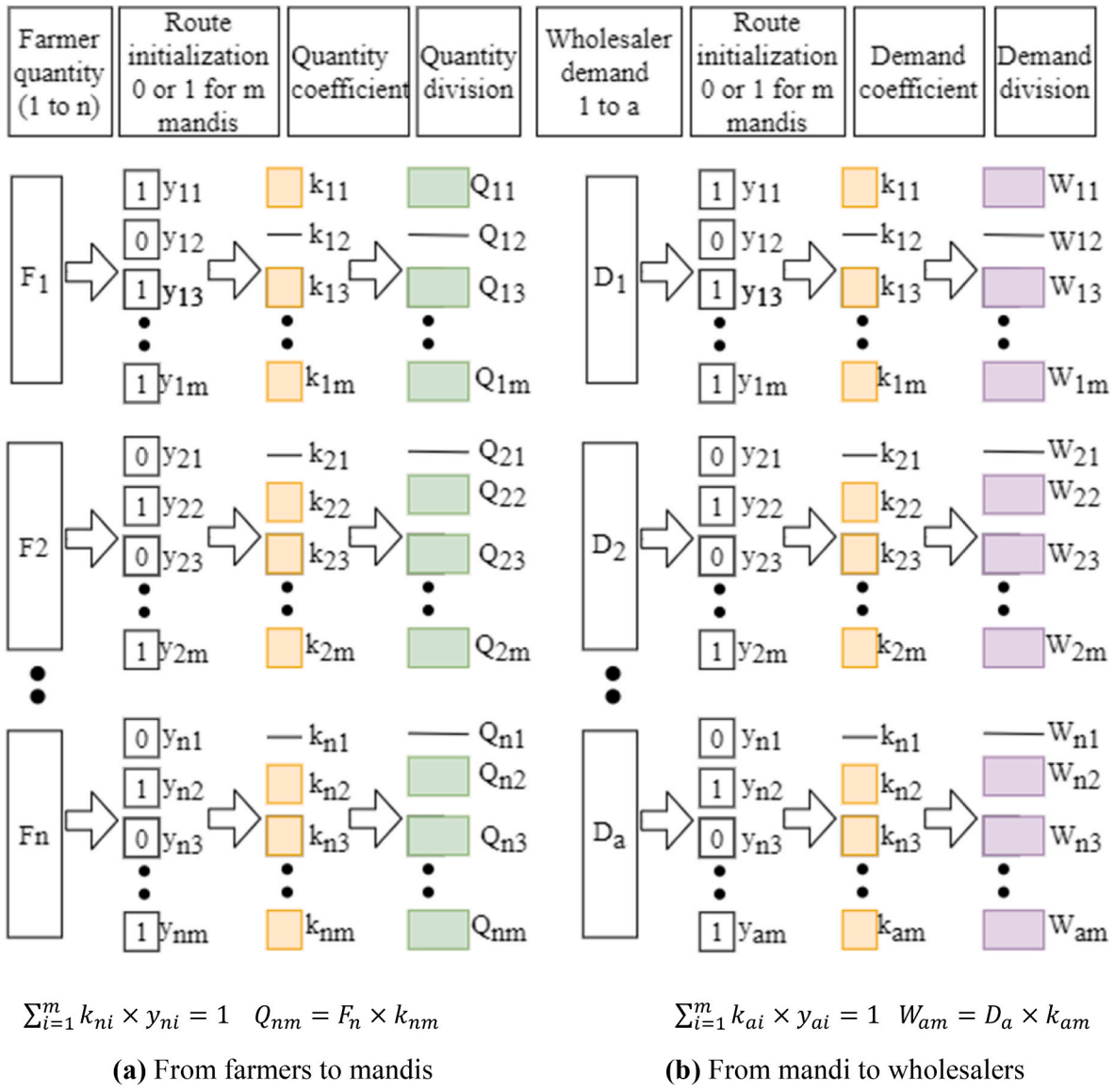



**Fig. 3.** Initialization of decision variables.

transportation from farmers to mandis, then from mandis to surplus and deficit state wholesalers via fixed, variable, and operational costs at the mandi and wholesaler levels. The second objective function (2) computes the TT it takes to travel by road from farmers to mandis, and then from mandis to surplus and deficit state wholesalers. Constraint (3) ensures that the total amount of food shipped from each farmer to all available mandis is equal to or less than the farmer's maximum amount of food. Constraint (4) ensures that the total amount of food shipped from each mandi to all available surplus and deficit state wholesalers is equal to or less than the mandi's maximum quantity. Constraint (5) requires that the total quantities transported by road from a surplus state mandi to a deficit state wholesaler equal the deficit state's demand during that time period. Constraint (6) requires that total road quantities transported from surplus state mandi to surplus state wholesaler equal the demand for the given surplus state during that time period. Constraint (7) is a quantity balancing constraint that updates the total quantity available at mandi in a given time period. It increases the initial inventory by the amount received from farmers and decreases the initial inventory by the amount transported to the surplus wholesaler. Constraint (8) ensures the initial inventory sets to zero. Constraint (9) ensures that the total quantity transported from farmer to mandi in the given time period is limited to the maximum capacity of available trucks at mandi for farmer. Constraint (10) ensures that the total quantity transported from mandi to surplus state wholesaler in a given time period is limited to the maximum capacity of available trucks at surplus state wholesaler for mandi. Constraint (11) ensures that the total quantity transported from mandi to deficit state wholesaler in the given time period is limited to the maximum capacity of available trucks at deficit state wholesaler for mandi. Constraint (12) ensures that the total number of trucks used at mandi is limited to the maximum number of trucks available at mandi. Constraint (13) ensures that the total number of trucks used at surplus state wholesaler is limited to the maximum number of trucks available at surplus state wholesaler. Constraint (14) ensures that the total number of trucks used at deficit state wholesaler is limited to the maximum number of trucks available at deficit state wholesaler. Constraints (15)-(22) ensure that the truck with the highest capacity available is chosen first, as we have considered three different capacity types of trucks in this work. Domain constraints are constraints (23)-(25).

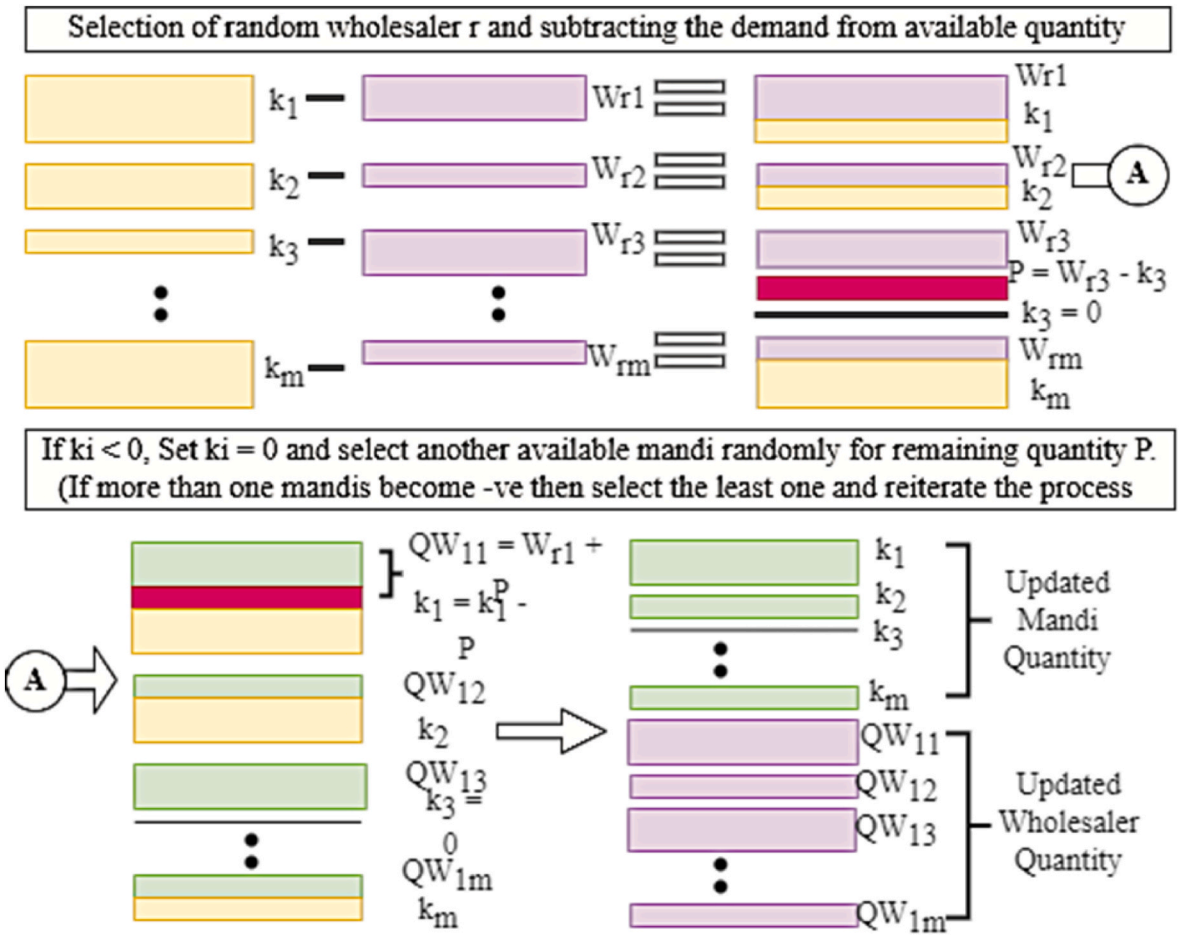



**Fig. 4.** Updating of decision variables according to availability constraints.

## 4. Methodology

This study presents a Mixed Integer Linear Programming (MILP) model that accurately reflects a Perishable Inventory Routing Problem (PIRP) scenario in real life. The Inventory Routing Problem (IRP) becomes NP-hard due to the increasing number of variables and constraints. Meta-heuristic algorithms are employed to tackle NP-hard problems in supply chain networks due to their complexity (Yavari et al., 2020; Wu et al., 2021; Seydanlou et al., 2022; dos Santos and Borenstein, 2022; Goodarzian et al., 2021; Hamid et al., 2023; Huang et al., 2023). In this study, the model was evaluated for 18 examples of large, medium, and small scenarios in the context of PIRP. However, with the exponential growth in the number of variables and constraints, the nature of the problem has become increasingly complex. To address this complexity, we propose a modified version of the NSGA-II algorithm (MNSGA-II) and compare its findings with the original NSGA-II. The superiority of the modified method is validated by calculating the percentage gap between them. Two primary factors influenced the selection of these algorithms:

(1) The primary difference between the proposed MNSGA-II with dynamic crowding distance and NSGA-II without dynamic crowding distance is the additional step of updating the crowding distance values after the selection step. This approach has the potential to benefit populations by preserving population diversity and preventing premature convergence.

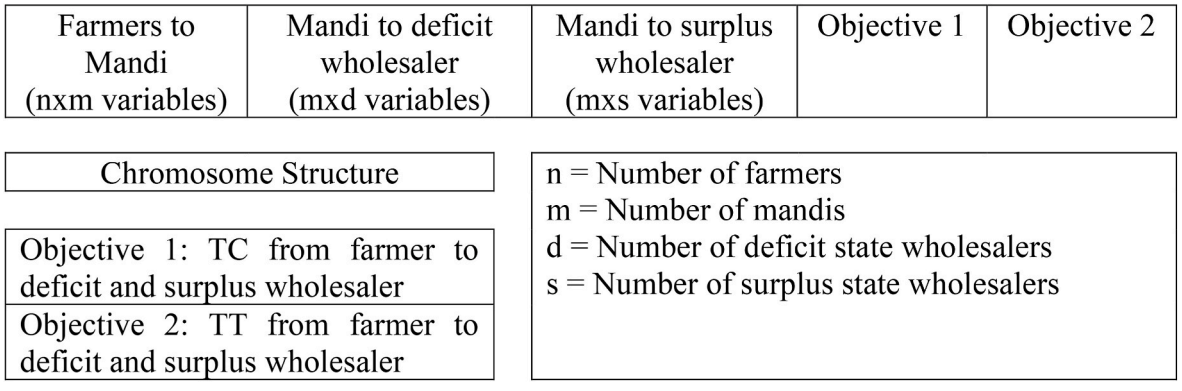



**Fig. 5.** Chromosome structure.

(2) To evaluate the efficacy of the proposed MNSGA-II algorithm, it must be compared to one of the most reliable and widely accepted algorithms. According to research, the NSGA-II algorithm is one of the best meta-heuristic algorithms for multiobjective optimization.

### 4.1. Modified non-dominated sorting genetic algorithm

After the selection step, the crowding distance values in this algorithm are updated based on the distance between individuals in the objective space. By giving more weight to individuals located further apart in the objective space, we can preserve population diversity and avoid premature convergence. By dynamically adjusting the crowding distance values, this version of the algorithm can adapt to changing problem characteristics and more effectively explore the entire Pareto front (Ramesh et al., 2012; Zhang et al., 2022; Wang et al., 2023). The procedure for implementing the proposed MNSGA-II is depicted in Fig. 2.

#### 4.1.1. Initialization of chromosome

Initially, the population was formed at random, with bits for each chromosome encoding the variables for a given population size. The equality criteria are met by generating each set of variables at random and then checking them against the inequality constraints. The set of variables is added to the chromosome if it meets the inequality criteria; otherwise, a new set of variables are generated at random. The cycle is repeated until the number of chromosomes produced equals the population size at the start. This section comprises two stages of chromosomes. Stage 1 involves the initialization of chromosomes from farmers to mandis, as illustrated in Fig. 3(a). Stage 2 pertains to the initialization of chromosomes from mandis to wholesalers, detailed in Fig. 3(b). Here's the detailed explanation for each stage:

*Stage 1:* Initialization of chromosome from farmer to mandi

1. Define the decision variable representing the amount of surplus state farmers' produce transported to different mandis. This variable determines the number of trucks required.
2. Initialize a random route variable (0 or 1); if it's 1, generate quantity coefficients randomly such that their sum equals 1.
3. Multiply the quantity coefficient by the total available quantity at the farmer's location to obtain the quantity decision variable, as shown in Fig. 3(a). Concatenate all decision variables into a single array.

*Stage 2:* Transfer of chromosome from mandi to wholesaler

1. The initialization process for the quantity transported from mandis to surplus and deficit state wholesalers is identical. However, only green tomatoes should be transported to deficit state wholesalers, while surplus state wholesalers receive the remaining tomatoes excluding waste.
2. Define the quantity transported from wholesalers to different mandis as a decision variable for initialization. The same variable is used for mandis to wholesalers, with the quantity determining the number of trucks required.
3. Initialize a random route variable (0 or 1); if it's 1, generate quantity coefficients randomly such that their sum equals 1.
4. Multiply the quantity coefficient by the total available quantity at the farmer's location to obtain the quantity decision variable, as depicted in Fig. 3(b).
5. Select a random wholesaler and subtract the quantity from the mandi's available stock. If the quantity becomes negative, acquire the excess from another mandi, as shown in Fig. 4.

#### 4.1.2. Tournament selection

Initially, n people are chosen at random, where n equals the tournament size, which is typically 2. Only one of these individuals is selected to join the mating pool. The order or position of the solutions is the primary criterion for selection. Lower-ranking solutions are chosen. When two people of the same rank are compared, the crowding distance is calculated. Individuals with a greater crowding distance are selected and added to the mating pool. From the mating pool, parents are chosen at random. Both the size of the mating pool and the size of the tournament affect the likelihood of producing fitter people. In this case, the size of the mating pool is (L/2), where L is the population size.

#### 4.1.3. Evolutionary operators

New solutions use crossover and mutation operators to create a child population of size L in order to improve the diversity of the population L. The crossover operator contributes to population variation and is used to investigate the possibility of unrated solutions to develop an answer significantly different from the previously evaluated solutions. A suitable crossover probability value is critical in ensuring the proposed algorithm's performance. The SBX operator has a crossover probability (Pc) of 0.9 (Deb and Agrawal, 1995; Martínez-Comesaña et al., 2023).

*4.1.3.1. Simulated binary crossover operator (SBX).* This SBX operator generates two children's solutions from two-parent solutions, which is analogous to a binary string one-point crossover (Gu et al., 2023; Zou et al., 2022; Cao et al., 2022; Deb and Agrawal, 1995). The procedure for obtaining two offspring solutions from two parents is as follows. A random number ($u$) between 0 and 1 is generated using a specific probability density function, and the ordinate is calculated so that the area under the probability density curve between 0 and 1 is chosen at random. The probability density function used to generate offspring solutions is nearly identical to the probability density function used in GA for single-point binary crossover. The probability density function is below.

$$\begin{aligned} p(\lambda) &= 0.5(\mu_c+1)\lambda^{\mu_c} \qquad \text{if } 0 \le \lambda \le 1 \\ p(\lambda) &= 0.5(\mu_c+1)\,{}^{1}\!/_{\lambda^{\mu_c+2}} \qquad \text{if } \lambda > 1 \end{aligned} \tag{26}$$

$\mu_c$ is a crossover distribution index in the preceding equation. Any non-negative real number can be used. A higher value of $\mu_c$ increases the likelihood of generating offspring that are similar to the parent, while a lower value of $\mu_c$ allows for the generation of offspring that are distant from their parent. The crossover distribution index of 20 is used in this study, as suggested by Hamdan (2014). We can find the $\lambda$ by equating the area under the probability density curve to the value of u in equation (27).

$$\lambda = \begin{cases} (2u)^{{}^{1}\!/_{\mu_c+1}} & \text{if } u \le 0.5 \\ \left({}^{1}\!/_{2(1-u)}\right)^{{}^{1}\!/_{\mu_c+1}} & \text{otherwise} \end{cases} \tag{27}$$

The offspring solutions are calculated after obtaining the above probability density function.

$$C_{1,k} = 0.5\left[(1-\lambda_k)p_{1,k} + (1+\lambda_k)p_{2,k}\right] \tag{28}$$

$$C_{2,k} = 0.5\left[(1-\lambda_k)p_{1,k} + (1+\lambda_k)p_{2,k}\right] \tag{29}$$

Here, $C_{i,k}$ is $i^{th}$ child of the $k^{th}$ variable of a chromosome. $p_{i,k}$ is the chosen parent, and $\lambda_k$ is a random number generated by the density function.

*4.1.3.2. Polynomial mutation operator.* Mutation is important because it protects the strongest individuals from diversification while improving the weakest. The mutation is typically performed to prevent the GA from falling to a local extreme, but it should not occur very frequently because the GA will become a random search. Raghuwanshi and Kakde (2006) and Martínez-Comesaña (2023) proposed a source mutation with a probability (Pk) of 0.10 as a mutation operator. The polynomial Mutation operator modifies each variable in accordance with the polynomial

distribution curve (Deb, 2001; Li et al., 2021) given by

$$\alpha_k = = \begin{cases} (2r_k)^{1/\mu_m + 1} & \text{if } r_k \leq 0.5 \\ 1 - (2(1 - r_k))^{1/\mu_m + 1} & \text{if } r_k > 0.5 \end{cases} \quad (30)$$

In this equation, $r_k$ is a random number between 0 and 1, $\mu_m$ is the mutation distribution index, and $\alpha_k$ is a small variation calculated from the polynomial distribution. Any non-negative real number can be used. A higher value of $\mu_m$ will produce offspring values close to the parent's upper limit, and vice versa. The mutation distribution index of 20 is considered in this work. $C_k$ is calculated using the following equation after calculating $\alpha_k$ from the above function child.

$$C_k = p_k + (p_k^u - p_k^l)\alpha_k \quad (31)$$

Here, $p_k$ is $k^{th}$ variable of the parent chromosome, and $p_k^u$ and $p_k^l$ are the $k^{th}$ variable's upper and lower limits. Following the generation of the offspring chromosome, a small set of variables is modified to satisfy the equality constraints, and the variables are tested against the inequality constraints. If all constraints are met, the modified variables are merged with the parent population; otherwise, the entire chromosome is discarded. The parent and child populations are then combined to form a new type of population. This ensures elitism, which results in a diverse group of people for better convergence. The new population is now subjected to a non-dominated sorting procedure, which divides the group of solutions into distinct non-dominated regions known as non-dominated fronts (Deb et al., 2002).

*4.1.3.3. Crowding distance (CD) and dynamic crowding distance (DCD).* Crowding distance aids in identifying distant spaces chromosomes, allowing for the selection of a sufficient number of unique chromosomes for the next generation.

$$CD_k = {}^1/_m \sum_{l=1}^{m} \left| g_{k+1}^l - g_{k-1}^l \right| \quad (32)$$

Where m is the number of objectives, $g_{k+1}^l$ is the k+1$^{th}$ individual of l$^{th}$ objective, and $g_{k-1}^l$ is the k-1$^{th}$ individual of l$^{th}$ objective after sorting the population corresponding to the CD (Deb et al., 2002; Biao et al., 2008; Ramesh et al., 2012). The main flaw of CD is the lack of consistent variability in the produced non-dominated solutions. The DCD approach is proposed to address this issue, and this involves removing the one with the lowest DCD value and recalculating DCD for the remaining ones each time (Luo et al., 2008). The DCD for each is calculated as follows:

$$DCD_k = CD_k \Big/ log\left({}^1/_{V_k}\right) \quad (33)$$

Where $V_k$ is the variance $CD_k$.

$$V_k = {}^1/_m \sum_{l=1}^{m} \left(g_{k+1}^l - g_{k-1}^l - CD_k\right)^2 \quad (34)$$

## 5. Computational study and results

In this section, we outline the computational experiments to reduce the TC and TT of PFP transportation from mandis to wholesalers. We detail the case study followed by the parameters setting and the experimental results. The methods were composed in MATLAB R2021b and tested on an Intel(R) Core (TM) i7-4790 processor with 8 GB of RAM. Both the NSGA-II and MNSGA-II algorithms were programmed to terminate after a maximum of 100 iterations in each run. All instances of the problem were solved using the NSGA-II and MNSGA-II, and the validity of the results was confirmed by comparing the proposed MNSGA-II results with the NSGA-II results.

**Table 2**
Distribution among differentiated scenarios.

| Category | Farmers (F) | Mandis *(M)* | Deficit state Wholesalers ($W_d$) | Surplus state Wholesalers ($W_s$) |
|---|---|---|---|---|
| Small | [1 to 30] | [2 to 4] | [2 3] | [1 2] |
| Medium | [40 to 60] | [2 to 4] | [2 3] | [1 2] |
| Large | [70 to 90] | [2 to 4] | [2 3] | [1 2] |

### 5.1. Case study

A study was conducted at the Madanapalle Tomato Market in Andhra Pradesh, India, renowned as one of the largest tomato markets in the country, to demonstrate the effectiveness of the proposed model and methodology in managing perishable goods in the PFSC. This market holds immense significance in agriculture due to its extensive tomato cultivation and trade activities. Renowned for its sprawling infrastructure and bustling trade, the market is a hub for tomato growers, traders, and buyers from diverse regions. The study comprehensively considered suppliers, mandis (marketplaces), and surplus and deficit wholesalers. Here, three problem scenarios were examined: small, medium, and large-scale, each comprising 18 instances, totaling 54 instances with escalating complexity (as depicted in Table 2). This data was categorized based on the number of surplus state farmers, mandis, and deficit and surplus state wholesalers involved in the supply chain. Three types of trucks were evaluated for transporting goods between locations, each with varying carrying capacities: 15,000 kg, 3000 kg, and 1000 kg of tomatoes. The one-time expenses associated with these trucks were ₹3366, ₹2785, and ₹2001, respectively. Additionally, the operating cost of the mandi was ₹0.133 per tomato, while the average truck price was ₹0.33 per kilometer per tomato.

### 5.2. Parameters setting based on Taguchi method

NSGA-II is a widely-used multi-objective optimization algorithm that has demonstrated its effectiveness in solving complex optimization problems with multiple conflicting objectives. The performance of NSGA-II is heavily influenced by the choice of key parameters such as Population Size, Crossover Probability, and Mutation Probability. Additionally, fine-tuning the Distribution Index for Crossover and Mutation is crucial for achieving optimal results (Deb and Agrawal 1999). Since a single set of meta heuristic algorithm parameters does not guarantee to obtain the near optimum solution of the problem, a Taguchi design method is conducted to tune the parameters. The orthogonal array (OA) and the signal-to-noise (S/N) ratio are the two main tools used in Taguchi design. The experimental schemes based on various levels of factors are contained in an OA, which is a numerical matrix. An important variation measure for this kind of experimental design is the S/N ratio. The Taguchi method seeks to simultaneously determine the optimal level of controllable parameters on the basis of robustness and reduce the influence of noise (Azadeh et al., 2017; Taheri and Taft, 2024). The goal of the Taguchi approach is to maximize the S/N ratio, which is determined for each parameter k on its corresponding level $l$ by using Eq. (35).

$$\left(S/N\right)_{kl} = -10 \log_{10}\left(\frac{\sum Z_{kl}^2}{n}\right) \forall k, l \quad (35)$$

The objective function value on level $l$ is represented by $Z_{kl}$, and the number of times level $l$ of parameter $k$ is repeated throughout all trial runs is denoted by $n$. To implement the chosen experimental design, the first step in parameter setting is to identify the parameters that will serve as control factors and their respective levels. Population size, crossover rate, mutation population rate, and number of iterations are among the parameters of the meta heuristic algorithm that are taken into

**Table 3**
Various metaheuristic parameter levels are applied for turning.

| Factors levels | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Population size | 200 | 300 | 400 | 500 |
| Iteration | 25 | 50 | 75 | 100 |
| Crossover rate | 0.8 | 0.85 | 0.9 | 0.95 |
| Mutation rate | 0.02 | 0.04 | 0.06 | 0.10 |

consideration for tuning. Table 3 displays the various tuning process levels for these parameters. $L_{16}\ (4^4)$ is selected as shown in Table 4 from the standard table of orthogonal arrays. The levels of each experimental scheme's parameters are indicated by rows in this table, while each scheme's specific, modifiable parameter level is indicated by column.

The suggested design is applied at four levels of each parameter, as indicated in Table 3, using Minitab 21 and sixteen distinct combinations of the constructed parameters. Table 4 provides a summary of the outcomes from the different parameter designs. The values with the largest S/N ratio are the best values because it's a minimization problem. The population size, number of generations, crossover and mutation rates (500, 100, 0.9, and 0.1, respectively) are determined to be optimal solution based on the selected Taguchi design based on the S/N ratio plot displayed in Fig. 6(a–b). The parameters used in Metaheuristic algorithms are listed in Table 5.

### 5.3. Computational results

The outcomes of the 18 occurrences of each issue from the three scenarios, along with the TC (Total Cost), TT (Total Time), and computing time, are presented in Tables 6–11. These tables illustrate that the TC and TT achieved using MNSGA-II are notably lower than those achieved using NSGA-II for every occurrence of each scenario.

#### 5.3.1. Small scale: Scenario I

In the first scenario of the two-level supply chain, mandis serve as intermediaries between farmers and wholesalers. Wholesalers are further categorized into surplus and deficit states. The placement of mandis and wholesalers is strategically determined in specific geographic regions with defined distances between them. Our supply chain model incorporates three types of trucks with different capacities: TC, which encompasses fixed, variable, and operational expenses; and TT. Table 6 compares the TC, TT, and CT (Computing Time) for NSGA-II and the proposed MNSGA-II. Table 7 presents the values of each decision variable used to evaluate the achievement of our objective.

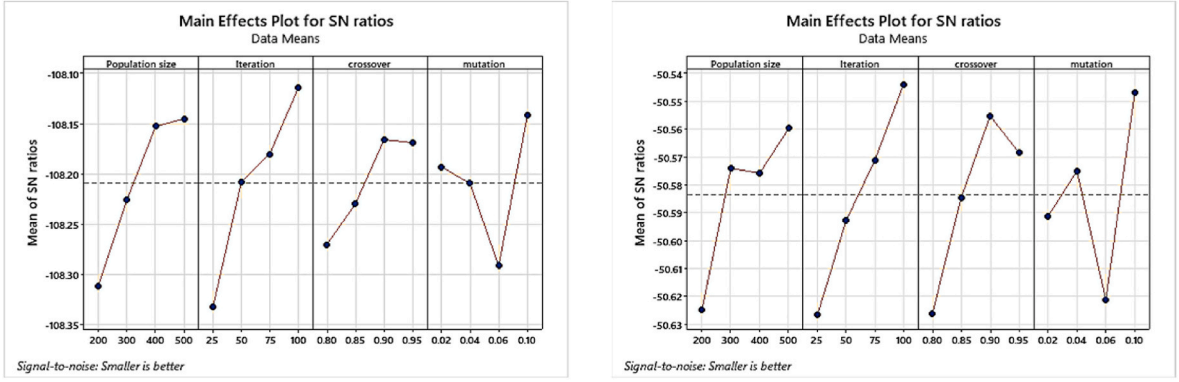
Table 6 reveals a notable trend where the CT increases as more

**Table 5**
Constant values for the parameters.

| Parameters | Values |
|---|---|
| Population | 500 |
| Generation (Iterations) | 100 |
| Crossover probability | 0.9 |
| mutation probability | 0.1 |
| Distribution index for crossover | 20 |
| Distribution Index for mutation | 20 |
| No of the objective function | 2 |
| Tolerance (No of products) | ±100 |

**Table 4**
Findings from various Taguchi approach designs.

| Design | Population size | Crossover rate | Mutation rate | Iteration numbers | TC | TT | SN(TC) | SN(TT) |
|---|---|---|---|---|---|---|---|---|
| 1 | 200 | 25 | 0.8 | 0.02 | 263770.03 | 342.88 | −108.425 | −50.7028 |
| 2 | 200 | 50 | 0.85 | 0.04 | 259642.91 | 338.5 | −108.288 | −50.5912 |
| 3 | 200 | 75 | 0.90 | 0.06 | 263076.24 | 340.61 | −108.402 | −50.6451 |
| 4 | 200 | 100 | 0.95 | 0.10 | 255090.88 | 337.32 | −108.134 | −50.5608 |
| 5 | 300 | 25 | 0.80 | 0.06 | 262467.74 | 339.06 | −108.382 | −50.6055 |
| 6 | 300 | 50 | 0.85 | 0.10 | 259087.68 | 338.18 | −108.269 | −50.5830 |
| 7 | 300 | 75 | 0.95 | 0.02 | 253859.84 | 336.38 | −108.092 | −50.5366 |
| 8 | 300 | 100 | 0.90 | 0.04 | 255898.41 | 337.72 | −108.161 | −50.5711 |
| 9 | 400 | 25 | 0.85 | 0.02 | 257050.35 | 338.02 | −108.200 | −50.5788 |
| 10 | 400 | 50 | 0.80 | 0.06 | 257633.81 | 340.79 | −108.220 | −50.6497 |
| 11 | 400 | 75 | 0.90 | 0.04 | 253076.42 | 335.66 | −108.065 | −50.5180 |
| 12 | 400 | 100 | 0.95 | 0.10 | 254886.24 | 337.17 | −108.127 | −50.5570 |
| 13 | 500 | 25 | 0.95 | 0.04 | 260753.05 | 339.62 | −108.325 | −50.6199 |
| 14 | 500 | 50 | 0.80 | 0.02 | 252818.34 | 336.79 | −108.056 | −50.5472 |
| 15 | 500 | 75 | 0.85 | 0.06 | 255966.07 | 338.26 | −108.164 | −50.5850 |
| 16 | 500 | 100 | 0.90 | 0.10 | 252266.28 | 334.47 | −108.037 | −50.4871 |




(a) Total Cost (TC) (b) Transportation Time (TT)

**Fig. 6.** Plot of S/N ratio derived from Taguchi design for TC and TT.

**Table 6**
TC, TT and CT obtained using NSGA-II and MNSGA-II for Scenario I.

| Instance | F-M-$W_d$-$W_s$ | No. of variables | Constraints | MNSGA-II | | | NSGA-II | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | TC | TT | CT | TC | TT | CT |
| 1 | 10-2-2-1 | 26 | 110 | 181139.56 | 223.13 | 8.53 | 184631.90 | 228.75 | 9.91 |
| 2 | 10-2-3-2 | 30 | 130 | 183051.46 | 227.75 | 8.77 | 187928.78 | 231.73 | 10.01 |
| 3 | 10-3-2-1 | 39 | 165 | 202979.55 | 254.30 | 9.60 | 207079.03 | 260.28 | 11.47 |
| 4 | 10-3-3-2 | 45 | 195 | 215244.03 | 270.33 | 9.78 | 220331.31 | 276.33 | 11.98 |
| 5 | 10-4-2-1 | 52 | 220 | 232273.43 | 293.50 | 10.81 | 236449.84 | 302.56 | 12.43 |
| 6 | 10-4-3-2 | 60 | 260 | 246861.67 | 326.47 | 11.36 | 252266.28 | 334.47 | 12.71 |
| 7 | 20-2-2-1 | 46 | 190 | 349073.13 | 396.65 | 11.04 | 355822.84 | 405.65 | 12.92 |
| 8 | 20-2-3-2 | 50 | 210 | 357457.66 | 414.50 | 11.66 | 364931.54 | 425.50 | 13.10 |
| 9 | 20-3-2-1 | 69 | 285 | 392142.05 | 452.50 | 12.67 | 399000.92 | 460.50 | 13.27 |
| 10 | 20-3-3-2 | 75 | 315 | 396118.01 | 456.21 | 13.31 | 403270.08 | 467.18 | 14.74 |
| 11 | 20-4-2-1 | 92 | 380 | 434283.17 | 503.63 | 14.69 | 441960.84 | 513.63 | 15.30 |
| 12 | 20-4-3-2 | 100 | 420 | 447511.87 | 547.25 | 15.28 | 456383.26 | 559.25 | 16.33 |
| 13 | 30-2-2-1 | 66 | 270 | 529731.36 | 589.48 | 13.87 | 537884.89 | 601.48 | 16.36 |
| 14 | 30-2-3-2 | 70 | 290 | 529882.32 | 650.71 | 13.72 | 542460.36 | 663.71 | 17.21 |
| 15 | 30-3-2-1 | 99 | 405 | 581042.71 | 667.28 | 16.03 | 591059.57 | 678.28 | 18.56 |
| 16 | 30-3-3-2 | 105 | 435 | 593820.62 | 744.13 | 16.22 | 602574.40 | 758.13 | 18.76 |
| 17 | 30-4-2-1 | 132 | 540 | 636081.19 | 744.96 | 18.33 | 644373.19 | 759.96 | 20.80 |
| 18 | 30-4-3-2 | 140 | 580 | 647746.39 | 818.84 | 19.55 | 659851.38 | 831.84 | 22.20 |
| Average | | | | 397580.01 | 476.76 | 13.07 | 404903.36 | 486.62 | 14.89 |

**Table 7**
Scenario I: Values of all the decision variables.

| P | F-M-$W_d$-$W_s$ | Fixed cost (F → M) | Variable cost (F → M) | Operational cost at M | Fixed cost (M → $W_d$) | Variable cost (M → $W_d$) | Operational cost at $W_d$ | Fixed cost (M → $W_s$) | Variable cost (M → $W_s$) | Operational cost at $W_s$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 10-2-2-1 | 75328 | 7181 | 12635 | 39231 | 21674 | 8313 | 19035 | 2168 | 3563 |
| 2 | 10-2-3-2 | 72891 | 6966 | 12635 | 33660 | 28009 | 8313 | 13464 | 3558 | 3563 |
| 3 | 10-3-2-1 | 84903 | 8546 | 12635 | 33660 | 27657 | 8313 | 20196 | 3508 | 3563 |
| 4 | 10-3-3-2 | 78462 | 7175 | 12635 | 47124 | 22434 | 8313 | 32499 | 3040 | 3563 |
| 5 | 10-4-2-1 | 95524 | 9874 | 12635 | 47124 | 22245 | 8313 | 29771 | 3228 | 3563 |
| 6 | 10-4-3-2 | 127498 | 8243 | 12635 | 33660 | 28623 | 8313 | 26928 | 3689 | 3563 |
| 7 | 20-2-2-1 | 147058 | 14012 | 23275 | 66159 | 40833 | 15313 | 32499 | 3749 | 6562 |
| 8 | 20-2-3-2 | 158085 | 16114 | 23275 | 53856 | 51812 | 15312 | 26928 | 6667 | 6562 |
| 9 | 20-3-2-1 | 188086 | 16962 | 23275 | 53856 | 51874 | 15313 | 33660 | 6488 | 6562 |
| 10 | 20-3-3-2 | 186113 | 16598 | 23275 | 64998 | 39113 | 15313 | 39231 | 4916 | 6562 |
| 11 | 20-4-2-1 | 220236 | 18070 | 23275 | 66159 | 51222 | 15313 | 26928 | 6519 | 6562 |
| 12 | 20-4-3-2 | 219830 | 17148 | 23275 | 72891 | 40179 | 15313 | 47124 | 5191 | 6562 |
| 13 | 30-2-2-1 | 220355 | 24711 | 35644 | 87516 | 78933 | 23450 | 39231 | 9993 | 10050 |
| 14 | 30-2-3-2 | 228654 | 24332 | 35644 | 93087 | 63972 | 23450 | 44802 | 5754 | 10050 |
| 15 | 30-3-2-1 | 277054 | 26978 | 35644 | 94248 | 61042 | 23450 | 45963 | 6615 | 10050 |
| 16 | 30-3-3-2 | 274847 | 28846 | 35644 | 87516 | 78878 | 23450 | 44396 | 10195 | 10050 |
| 17 | 30-4-2-1 | 320691 | 29107 | 35644 | 94248 | 62055 | 23450 | 52695 | 8141 | 10050 |
| 18 | 30-4-3-2 | 311756 | 31100 | 35644 | 94248 | 80251 | 23450 | 51128 | 10121 | 10050 |

variables and constraints are introduced into the problem, highlighting the computational complexity of the SC optimization task. Additionally, the escalation in the number of farmers correlates with heightened TC and TT expenses, primarily due to the increased need for transporting goods, resulting in elevated transportation costs and time from the farmer to the mandi. However, the geographical placements of mandis and wholesalers wield significant influence over the supply chain's overall cost and transportation time. Notably, MNSGA-II consistently outperforms NSGA-II across all instances in TC and TT, indicating its efficacy in optimizing the SC and delivering lower costs and shorter transportation times. This underscores the importance of employing advanced optimization algorithms like MNSGA-II, particularly in complex SC scenarios where efficiency and cost-effectiveness are critical.

Table 7 provides insights into the values of all decision variables for

**Table 8**
TC, TT and CT obtained using NSGA-II and MNSGA-II for Scenario II.

| Instance | F-M-$W_d$-$W_s$ | No. of variables | Constraints | MNSGA-II | | | NSGA-II | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | TC | TT | CT | TC | TT | CT |
| 1 | 40-2-2-1 | 86 | 350 | 687763.38 | 725.37 | 16.37 | 702413.38 | 740.37 | 17.12 |
| 2 | 40-2-3-2 | 90 | 370 | 703673.70 | 827.51 | 16.61 | 723426.70 | 848.51 | 18.26 |
| 3 | 40-3-2-1 | 129 | 525 | 755103.54 | 842.14 | 18.64 | 772923.57 | 861.14 | 20.83 |
| 4 | 40-3-3-2 | 135 | 555 | 779535.69 | 890.05 | 19.24 | 799335.72 | 916.05 | 21.10 |
| 5 | 40-4-2-1 | 172 | 700 | 817945.64 | 938.38 | 19.28 | 835006.00 | 958.38 | 22.24 |
| 6 | 40-4-3-2 | 180 | 740 | 874474.77 | 968.31 | 19.97 | 897635.77 | 997.31 | 22.83 |
| 7 | 50-2-2-1 | 106 | 430 | 881411.54 | 1021.29 | 19.75 | 905687.54 | 1047.29 | 23.13 |
| 8 | 50-2-3-2 | 110 | 450 | 920448.87 | 1041.21 | 21.01 | 938773.97 | 1068.21 | 24.58 |
| 9 | 50-3-2-1 | 159 | 645 | 939421.27 | 1048.59 | 21.51 | 959290.35 | 1073.59 | 24.84 |
| 10 | 50-3-3-2 | 165 | 675 | 976767.00 | 1052.47 | 21.81 | 1000908.11 | 1086.47 | 25.99 |
| 11 | 50-4-2-1 | 212 | 860 | 1012502.90 | 1129.09 | 22.78 | 1037167.19 | 1165.09 | 26.74 |
| 12 | 50-4-3-2 | 220 | 900 | 1057265.29 | 1143.97 | 23.11 | 1079109.19 | 1183.97 | 27.09 |
| 13 | 60-2-2-1 | 126 | 510 | 1059068.80 | 1181.46 | 23.03 | 1084131.26 | 1210.46 | 28.77 |
| 14 | 60-2-3-2 | 130 | 530 | 1064051.16 | 1219.47 | 23.65 | 1092189.41 | 1255.47 | 28.84 |
| 15 | 60-3-2-1 | 189 | 765 | 1136820.42 | 1284.33 | 23.97 | 1159567.62 | 1326.33 | 29.31 |
| 16 | 60-3-3-2 | 195 | 795 | 1177402.29 | 1312.88 | 25.22 | 1203372.29 | 1342.88 | 29.53 |
| 17 | 60-4-2-1 | 252 | 1020 | 1249215.06 | 1353.61 | 27.10 | 1285299.06 | 1388.61 | 33.24 |
| 18 | 60-4-3-2 | 260 | 1060 | 1293847.36 | 1453.27 | 27.59 | 1320097.36 | 1492.27 | 33.23 |
| Average | | | | 965928.82 | 1079.63 | 21.70 | 988685.25 | 1109.02 | 25.43 |

**Table 9**
Scenario II: Values of all the decision variables.

| P | F-M-$W_d$-$W_s$ | Fixed cost (F → M) | Variable cost (F → M) | Operational cost at M | Fixed cost (M → $W_d$) | Variable cost (M → $W_d$) | Operational cost at $W_d$ | Fixed cost (M → $W_s$) | Variable cost (M → $W_s$) | Operational cost at $W_s$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 40-2-2-1 | 319534 | 32681 | 45353 | 107712 | 81419 | 29837 | 51128 | 7312 | 12788 |
| 2 | 40-2-3-2 | 315009 | 32676 | 45353 | 107712 | 100450 | 29837 | 47124 | 12725 | 12788 |
| 3 | 40-3-2-1 | 357313 | 33490 | 45353 | 116126 | 100225 | 29837 | 47124 | 12848 | 12788 |
| 4 | 40-3-3-2 | 401824 | 36805 | 45353 | 107712 | 78934 | 29837 | 57860 | 8423 | 12788 |
| 5 | 40-4-2-1 | 413138 | 36457 | 45353 | 126747 | 77065 | 29837 | 66159 | 10402 | 12788 |
| 6 | 40-4-3-2 | 417671 | 39895 | 57323 | 134640 | 101094 | 37713 | 60588 | 9389 | 16163 |
| 7 | 50-2-2-1 | 474186 | 37125 | 45353 | 114444 | 100878 | 29837 | 53856 | 12944 | 12788 |
| 8 | 50-2-3-2 | 432468 | 39198 | 57323 | 134640 | 126513 | 37713 | 60588 | 15847 | 16163 |
| 9 | 50-3-2-1 | 471232 | 39378 | 57323 | 146943 | 98527 | 37713 | 60588 | 11555 | 16163 |
| 10 | 50-3-3-2 | 479125 | 44294 | 57323 | 134640 | 126571 | 37713 | 64592 | 16348 | 16163 |
| 11 | 50-4-2-1 | 470596 | 43224 | 68495 | 161568 | 119266 | 45063 | 74052 | 10927 | 19312 |
| 12 | 50-4-3-2 | 564200 | 40213 | 57323 | 148104 | 97911 | 37713 | 82466 | 13174 | 16163 |
| 13 | 60-2-2-1 | 551721 | 40705 | 57323 | 140211 | 126244 | 37713 | 72891 | 16099 | 16163 |
| 14 | 60-2-3-2 | 490792 | 46554 | 68495 | 154836 | 152202 | 45063 | 67320 | 19477 | 19313 |
| 15 | 60-3-2-1 | 578476 | 49273 | 68495 | 167139 | 116943 | 45062 | 78056 | 14064 | 19312 |
| 16 | 60-3-3-2 | 593565 | 43415 | 68495 | 161568 | 152053 | 45063 | 74052 | 19880 | 19313 |
| 17 | 60-4-2-1 | 680556 | 45371 | 68495 | 168300 | 117415 | 45063 | 87631 | 17073 | 19312 |
| 18 | 60-4-3-2 | 700227 | 42067 | 68495 | 168300 | 152832 | 45063 | 78056 | 19495 | 19313 |

each scenario within the SC model. Observing the fixed and variable costs associated with transportation between different entities (farmers, mandis, wholesalers) and the operational costs at mandis and wholesalers reveals patterns influenced by the scenario configurations. For instance, as the number of farmers or mandis increases, the fixed and variable costs tend to rise accordingly, reflecting the expanded scope of operations. Additionally, variations in the geographical placements of mandis and wholesalers impact operational costs, with different scenarios yielding distinct cost structures. These observations highlight the intricate interplay between scenario parameters and cost dynamics within the SC, emphasizing the importance of meticulous optimization to mitigate expenses and enhance efficiency.

**Table 10**
TC, TT, and CT obtained using NSGA-II and MNSGA-II for Scenario III.

| Instance | F-M-$W_d$-$W_s$ | No. of variables | Constraints | MNSGA-II | | | NSGA-II | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | TC | TT | CT | TC | TT | CT |
| 1 | 70-2-2-1 | 146 | 590 | 1225145.46 | 1254.04 | 24.84 | 1258775.60 | 1282.04 | 29.89 |
| 2 | 70-2-3-2 | 150 | 610 | 1259684.90 | 1407.41 | 25.04 | 1289573.15 | 1457.41 | 31.25 |
| 3 | 70-3-2-1 | 219 | 885 | 1325456.19 | 1444.57 | 27.86 | 1352353.29 | 1479.57 | 32.61 |
| 4 | 70-3-3-2 | 225 | 915 | 1374865.21 | 1453.85 | 27.82 | 1406800.73 | 1513.85 | 33.67 |
| 5 | 70-4-2-1 | 292 | 1180 | 1380071.68 | 1590.01 | 29.97 | 1412282.68 | 1626.01 | 35.07 |
| 6 | 70-4-3-2 | 300 | 1220 | 1463043.44 | 1601.14 | 30.31 | 1508671.71 | 1633.14 | 35.66 |
| 7 | 80-2-2-1 | 166 | 670 | 1494981.98 | 1630.62 | 30.10 | 1537355.30 | 1666.62 | 38.20 |
| 8 | 80-2-3-2 | 170 | 690 | 1539949.59 | 1674.71 | 31.13 | 1576342.74 | 1710.71 | 39.81 |
| 9 | 80-3-2-1 | 249 | 1005 | 1577456.77 | 1729.04 | 33.92 | 1616874.21 | 1797.04 | 39.84 |
| 10 | 80-3-3-2 | 255 | 1035 | 1620505.05 | 1736.72 | 34.85 | 1657735.05 | 1812.72 | 41.66 |
| 11 | 80-4-2-1 | 332 | 1340 | 1628213.04 | 1850.04 | 35.66 | 1664849.04 | 1887.04 | 42.01 |
| 12 | 80-4-3-2 | 340 | 1380 | 1645316.38 | 1867.99 | 35.90 | 1689864.96 | 1956.99 | 42.15 |
| 13 | 90-2-2-1 | 186 | 750 | 1731354.28 | 1884.58 | 36.12 | 1775507.28 | 1927.58 | 42.94 |
| 14 | 90-2-3-2 | 190 | 770 | 1746428.72 | 1930.27 | 38.04 | 1790638.72 | 1972.27 | 43.90 |
| 15 | 90-3-2-1 | 279 | 1125 | 1755674.37 | 2081.35 | 38.58 | 1798520.57 | 2140.35 | 44.28 |
| 16 | 90-3-3-2 | 285 | 1155 | 1840612.45 | 2082.12 | 41.28 | 1911710.48 | 2163.12 | 45.23 |
| 17 | 90-4-2-1 | 372 | 1500 | 1979369.34 | 2126.17 | 52.41 | 2038971.40 | 2193.17 | 57.92 |
| 18 | 90-4-3-2 | 380 | 1540 | 2003834.51 | 2358.58 | 52.92 | 2102173.51 | 2410.58 | 58.92 |
| Average | | | | 1588442.41 | 1761.29 | 34.82 | 1632722.24 | 1812.79 | 40.83 |

**Table 11**
Scenario III: Values of all the decision variables.

| P | F-M-$W_d$-$W_s$ | Fixed cost (F → M) | Variable cost (F → M) | Operational cost at M | Fixed cost (M → $W_d$) | Variable cost (M → $W_d$) | Operational cost at $W_d$ | Fixed cost (M → $W_s$) | Variable cost (M → $W_s$) | Operational cost at $W_s$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 70-2-2-1 | 575522 | 53115 | 82194 | 194067 | 143445 | 54075 | 86355 | 13198 | 23175 |
| 2 | 70-2-3-2 | 567744 | 53327 | 82194 | 188496 | 182558 | 54075 | 84788 | 23328 | 23175 |
| 3 | 70-3-2-1 | 651080 | 54048 | 82194 | 200799 | 145139 | 54075 | 95930 | 19017 | 23175 |
| 4 | 70-3-3-2 | 664368 | 56890 | 82194 | 195228 | 182236 | 54075 | 93087 | 23612 | 23175 |
| 5 | 70-4-2-1 | 612374 | 59419 | 97223 | 228888 | 170161 | 63963 | 105390 | 15242 | 27412 |
| 6 | 70-4-3-2 | 649517 | 64672 | 97223 | 222156 | 216148 | 63962 | 94248 | 27704 | 27412 |
| 7 | 80-2-2-1 | 819835 | 59785 | 82194 | 201960 | 143435 | 54075 | 93087 | 17436 | 23175 |
| 8 | 80-2-3-2 | 826568 | 56967 | 82194 | 200799 | 179910 | 54075 | 93087 | 23175 | 23175 |
| 9 | 80-3-2-1 | 801444 | 62795 | 97223 | 232892 | 166360 | 63963 | 99819 | 25550 | 27412 |
| 10 | 80-3-3-2 | 766570 | 72398 | 109060 | 249084 | 191666 | 71750 | 111716 | 17511 | 30750 |
| 11 | 80-4-2-1 | 809916 | 64584 | 97223 | 222156 | 214425 | 63962 | 100980 | 27554 | 27412 |
| 12 | 80-4-3-2 | 735117 | 68336 | 109060 | 249084 | 242442 | 71750 | 107712 | 31065 | 30750 |
| 13 | 90-2-2-1 | 834698 | 71281 | 109060 | 266552 | 192572 | 71750 | 124425 | 30266 | 30750 |
| 14 | 90-2-3-2 | 947334 | 71130 | 97223 | 235620 | 168942 | 63963 | 112122 | 22683 | 27412 |
| 15 | 90-3-2-1 | 921336 | 66399 | 97223 | 230570 | 213402 | 63962 | 107712 | 27658 | 27412 |
| 16 | 90-3-3-2 | 912693 | 71883 | 109060 | 255816 | 243272 | 71750 | 114444 | 30944 | 30750 |
| 17 | 90-4-2-1 | 1107388 | 75527 | 109060 | 254655 | 187403 | 71750 | 114444 | 28392 | 30750 |
| 18 | 90-4-3-2 | 1074717 | 76212 | 109060 | 255816 | 239898 | 71750 | 114444 | 31187 | 30750 |

#### 5.3.2. Medium scale: Scenario II

Tables 8 and 9 displays results for the Scenario II. Here, we observe a consistent trend where the TC and TT increase as the complexity of the scenario, indicated by the number of variables and constraints, escalates. Moreover, the proposed MNSGA-II consistently demonstrates lower TC and TT compared to NSGA-II across all instances, highlighting its superior performance in optimizing the supply chain for Scenario II.

#### 5.3.3. Large scale: Scenario III

Table 10 follows a similar structure to Tables 6 and 8, presenting the TC, TT, and CT obtained using NSGA-II and MNSGA-II for Scenario III across different instances. However, notable differences are observed in the values of TC, TT, and CT compared to the previous scenarios. In Scenario III, the instances involve higher numbers of farms, mandis, wholesalers, and states, leading to increased complexity in the

**Table 12**
The three scenarios average values of TC, TT, and CT - comparative analysis.

| Scenario | MNSGA-II | | | NSGA-II | | |
|---|---|---|---|---|---|---|
| | TC | TT | CT | TC | TT | CT |
| Small | 397580.01 | 476.76 | 13.07 | 404903.36 | 486.62 | 14.89 |
| Medium | 965928.82 | 1079.63 | 21.70 | 988685.25 | 1109.02 | 25.43 |
| Large | 1588442.41 | 1761.29 | 34.82 | 1632722.24 | 1812.79 | 40.83 |

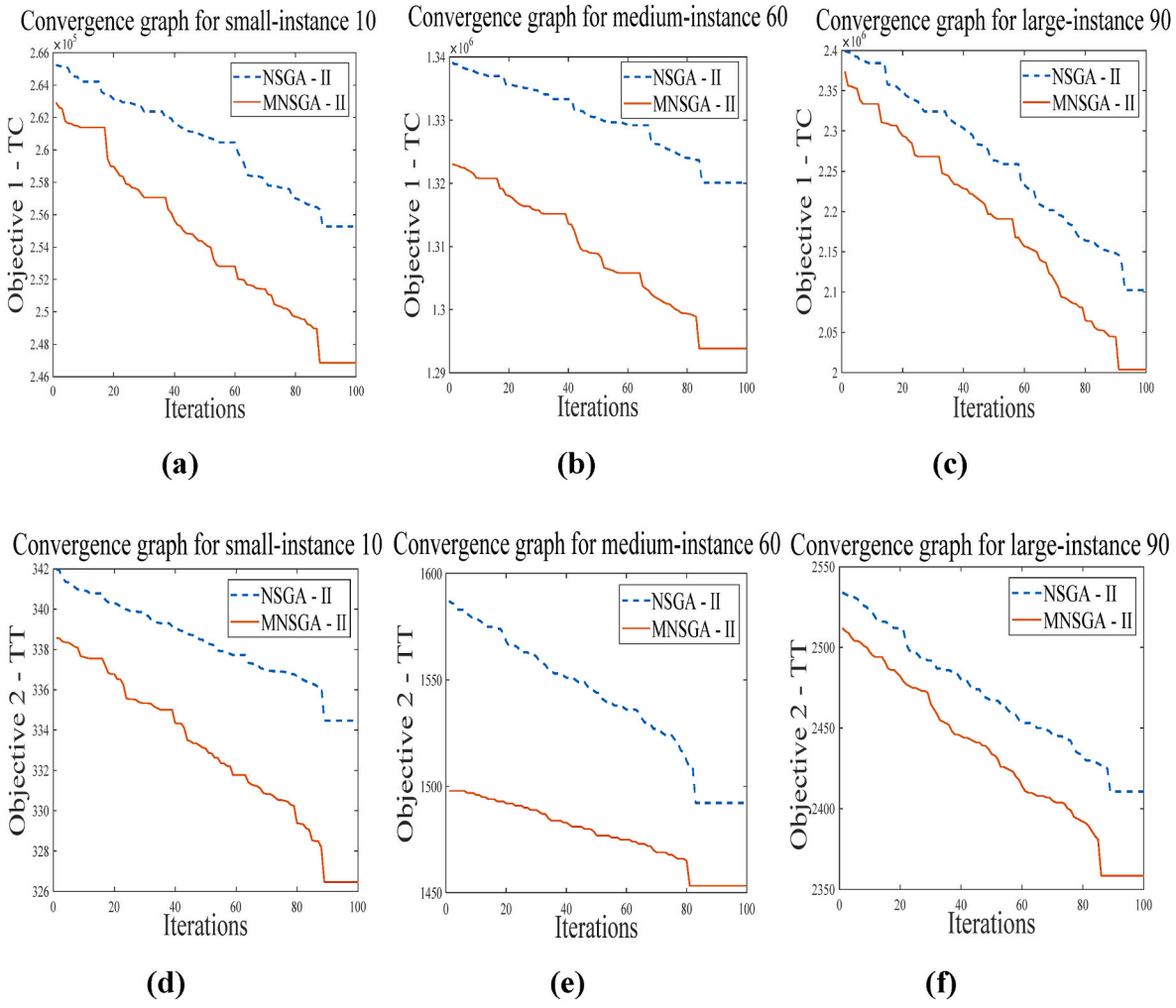



**Fig. 7.** (a)–**(c).** $10^{th}$, $18^{th}$ and $18^{th}$ instances of small, medium and large scenarios of TC convergence graphs. Fig. 7(d) to **(f).** $10^{th}$, $18^{th}$ and $18^{th}$ instances of small, medium and large scenarios of TT convergence graphs.

optimization problem. Consequently, we observe higher values of TC and TT across all instances compared to Scenarios I and II. Additionally, the CT also tends to be higher, reflecting the increased computational requirements due to the larger number of variables and constraints. Despite these challenges, MNSGA-II consistently outperforms NSGA-II in terms of TC and TT, showcasing its effectiveness in optimizing supply chain operations even in complex scenarios. However, it's noteworthy that the gap between MNSGA-II and NSGA-II in terms of TC and TT appears to be narrower in Scenario III compared to the previous scenarios, indicating that the benefits of MNSGA-II may diminish slightly as the complexity of the problem increases.

Table 11 provides an overview of the values associated with all decision variables for Scenario III across different instances within the SC model. Analyzing the fixed and variable costs involved in transportation between various entities such as farms, mandis, and wholesalers, along with the operational costs at mandis and wholesalers, reveals insights into the cost structures within Scenario III. We observe variations in these costs depending on the configurations of farms, mandis, and wholesalers, indicating the influence of scenario parameters on cost dynamics. As the scenario becomes more complex, characterized by higher numbers of farms, mandis, and wholesalers, we observe corresponding increases in fixed and variable costs.

### 5.4. Comparative analysis of all three scenarios

This study focuses on two key aspects: inventory routing of the PFP from farmers to wholesalers, considering surplus and deficit states, and minimizing TC and TT using NSGA-II and MNSGA-II. Additionally, these meta-heuristic algorithms' CT is computed. Table 12 illustrates the average difference in TC, TT, and CT between the two algorithms for each problem instance across the scenarios. As complexity increases, reflected in the increased number of required products, TC, TT, and CT

**Table 13**
Three scenarios comparative analysis - % Gap.

| Instances | % Gap - Small | | | % Gap - Medium | | | % Gap - Large | | |
|---|---|---|---|---|---|---|---|---|---|
| | TC | TT | CT | TC | TT | CT | TC | TT | CT |
| 1 | 1.93 | 2.52 | 16.23 | 2.13 | 2.07 | 4.59 | 2.74 | 2.23 | 20.31 |
| 2 | 2.66 | 1.75 | 14.06 | 2.81 | 2.54 | 9.94 | 2.37 | 3.55 | 24.77 |
| 3 | 2.02 | 2.35 | 19.46 | 2.36 | 2.26 | 11.74 | 2.03 | 2.42 | 17.02 |
| 4 | 2.36 | 2.22 | 22.45 | 2.54 | 2.92 | 9.70 | 2.32 | 4.13 | 21.02 |
| 5 | 1.80 | 3.09 | 14.97 | 2.09 | 2.13 | 15.33 | 2.33 | 2.26 | 17.04 |
| 6 | 2.19 | 2.45 | 11.93 | 2.65 | 2.99 | 14.34 | 3.12 | 2.00 | 17.66 |
| 7 | 1.93 | 2.27 | 17.01 | 2.75 | 2.55 | 17.14 | 2.83 | 2.21 | 26.91 |
| 8 | 2.09 | 2.65 | 12.33 | 1.99 | 2.59 | 16.97 | 2.36 | 2.15 | 27.88 |
| 9 | 1.75 | 1.77 | 4.80 | 2.12 | 2.38 | 15.48 | 2.50 | 3.93 | 17.43 |
| 10 | 1.81 | 2.40 | 10.81 | 2.47 | 3.23 | 19.16 | 2.30 | 4.38 | 19.53 |
| 11 | 1.77 | 1.99 | 4.17 | 2.44 | 3.19 | 17.39 | 2.25 | 2.00 | 17.81 |
| 12 | 1.98 | 2.19 | 6.87 | 2.07 | 3.50 | 17.21 | 2.71 | 4.76 | 17.41 |
| 13 | 1.54 | 2.04 | 17.94 | 2.37 | 2.45 | 24.92 | 2.55 | 2.28 | 18.88 |
| 14 | 2.37 | 2.00 | 25.37 | 2.64 | 2.95 | 21.92 | 2.53 | 2.18 | 15.39 |
| 15 | 1.72 | 1.65 | 15.82 | 2.00 | 3.27 | 22.29 | 2.44 | 2.83 | 14.77 |
| 16 | 1.47 | 1.88 | 15.69 | 2.21 | 2.29 | 17.09 | 3.86 | 3.89 | 9.57 |
| 17 | 1.30 | 2.01 | 13.48 | 2.89 | 2.59 | 22.64 | 3.01 | 3.15 | 10.51 |
| 18 | 1.87 | 1.59 | 13.55 | 2.03 | 2.68 | 20.47 | 4.91 | 2.20 | 11.34 |
| AVG | 1.92 | 2.16 | 14.27 | 2.36 | 2.70 | 16.57 | 2.73 | 2.92 | 18.07 |

also rise. Fig. 7(a–f) displays the convergence graph for the tenth, eighteenth, and eighteenth instances of small, medium, and large scenarios. Notably, MNSGA-II exhibits a faster convergence rate compared to NSGA-II, as evident from the graphs. The horizontal axis represents the number of iterations, while the vertical axis represents TC and TT. Additionally, Table 13 presents the percentage gaps for the three scenarios.

Table 13 presents the percentage gaps for the three scenarios, comparing the results obtained by MNSGA-II with the NSGA-II obtained by solving the MILP formulation. Analyzing the values reveals that, on average, MNSGA-II achieves a percentage gap of 1.92% for TC, 2.16% for TT, and 14.27% for CT across all scenarios. These values suggest that, on average, the solutions obtained by the proposed MNSGA-II are within approximately 2% of the optimal solution for TC and TT and approximately 14% computationally faster than NSGA-II. Moreover, the percentage gaps vary across different instances and scenarios, reflecting the influence of problem complexity on the performance of MNSGA-II. Overall, the results indicate that MNSGA-II provides solutions that are very close to the optimal solution obtained by the MILP formulation, demonstrating its effectiveness in efficiently solving the inventory routing problem.

Fig. 7(a–f) illustrates the trend of TC and TT as the number of generations increases. There is a notable decrease in these values until they stabilize after reaching a certain threshold. Due to the varying complexity of each problem instance depending on the algorithm employed, it is unreasonable to assume that fewer generations will lead to faster computation. To ensure a fair evaluation, an equal number of generations was utilized for both algorithms. Our findings demonstrate that MNSGA-II surpasses NSGA-II in terms of TC, TT, and CT when applied to the proposed MILP model for the PIRP. Consequently, we can conclude that the proposed MNSGA-II is a more suitable algorithm for addressing this problem.

### 5.5. Managerial insights

This section delves into the economic significance of the cost improvements achieved through our optimization efforts and the broader implications for managing PFP in the PFSC. Effective inventory management is crucial for minimizing waste and ensuring the timely delivery of PFP. It is essential for stakeholders to have a clear understanding of demand requirements for PFP and to align transportation accordingly. Collaboration among all PFSC stakeholders is vital to guarantee the efficient and timely delivery of PFP.

*Economic Interpretation of Cost Improvements:* Our optimization efforts resulted in significant cost reductions across different scenarios. In the small scenario, the TC decreased by $7323.25, from $404,903.36 to $397,580.01. Similarly, in the medium and large scenarios, costs were reduced by $22,756.43 and $44,279.84, respectively. These cost savings demonstrate the tangible economic benefits of our optimization approach and highlight the potential for significant cost reductions in managing perishable food products within the PFSC. Specifically, by minimizing expenses associated with transportation, inventory management, and operational inefficiencies, our model unlocks significant cost-saving opportunities for stakeholders in the PFSC.

*Economic Interpretation of Time Reduction:* The reduction in TT achieved through our optimization efforts yields significant economic benefits within the PFSC. Our approach enhances operational efficiency and resource utilization by streamlining transportation routes, minimizing waiting times, and optimizing resource allocation. This can save costs through reduced operational expenses such as labour, fuel, and vehicle maintenance. Moreover, faster delivery times can prevent the shelf life of the products by meeting demand promptly and reliably. Additionally, the enhanced market responsiveness enables stakeholders to capitalize on emerging opportunities and adapt swiftly to changing market conditions.

## 6. Conclusions

In today's world, the optimization of inventory routing plays a critical role in efficiently meeting the demand for perishable products within the PFSC. Effective inventory routing is essential to address perishability issues and to reduce delivery times. By strategically managing inventory routing, businesses can effectively mitigate perishability concerns and ensure timely delivery of these sensitive products, ultimately meeting consumer demands with precision. The objective of the study is to optimize the TC and TT for PIRP, precisely delivering perishable goods from surplus to deficit and surplus wholesalers.

Our study was centered around the Indian PFSC model, where farmers in surplus regions utilize intermediary mandis to distribute their produce to surplus and deficit wholesalers. In this regard, we developed several problem instances categorized into small, medium, and large scenarios for broad applicability. Subsequently, we formulated a MILP model for the PIRP to optimize TC and TT while adhering to various constraints. Given the NP-hard nature of this problem, we adopted a meta-heuristic evolutionary algorithmic approach. Our proposed algorithm, MNSGA-II, was a modified version of NSGA-II, allowing for a

more efficient comparison. Upon comparison, the proposed MNSGA-II demonstrated superior performance over NSGA-II, showcasing its effectiveness in tackling the complexities of the PFSC optimization problem.

The findings from this study offer valuable insights for practitioners and researchers in the food industry, aiding in the development and refinement of supply chain management strategies. However, there are certain limitations that need to be acknowledged. Firstly, focusing solely on one product for this study limits its applicability. To address a broader range of real-world issues, future studies should consider examining multiple products within the PIRP framework. Additionally, this study's consideration of deterministic demand overlooks the uncertainty inherent in real-world scenarios. Future research in the PIRP domain should incorporate demand uncertainty to provide more robust solutions. For further exploration, this study suggests three areas of focus: (1) quantifying performance indicators to estimate the ripple effect of the current model. (2) integrating disruptions in farmers and mandis to assess their impact. (3) expanding the study's scope and relevance by considering a multi-food type category.

## CRediT authorship contribution statement

**Malleswari Karanam:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lanka Krishnanand:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Vijaya Kumar Manupati:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **M.L.R. Varela:** Writing – review & editing, Visualization, Validation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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