Configuring a Circular Economy-based Reverse Logistics Network for the Agri-food Industry based on the Agility and Resilience Dimensions

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Abstract

This study develops a comprehensive circular economy–based reverse logistics network for apple by explicitly integrating agility and resilience considerations under mixed uncertainty. The proposed network encompasses multiple echelons, including farms, collection centers, recycling centers, animal husbandry units, and energy and compost demand points, enabling effective waste recovery and value creation. A multi-objective mathematical programming model is formulated to simultaneously maximize economic performance, minimize node criticality as a proxy for resilience, and enhance service levels as an indicator of agility. To address the inherent uncertainty in parameters, a robust stochastic–possibilistic optimization framework is employed. Furthermore, the model is solved using a recently developed method named the Fuzzy Multi-Choice Chebyshev Goal Programming with Utility Function (FMCCGP-UF) method. The practical relevance of the proposed approach is validated through its application to a real-world case study of the apple reverse supply chain in Iran. Results reveal that increasing processing and collection capacities improve economic outcomes while simultaneously strengthening agility and resilience. The network design leads to the establishment of recycling centers #2 and #5, as well as collection centers #1, #3, and #4. Critical nodes are identified as recycling center #2 (periods 2 and 5) and collection center #1 (periods 3 and 5) and collection center #2 (periods 1 and 5). The service levels achieved are 0.73 for animal husbandry units, 0.78 for compost demand points, and 0.69 for energy demand points. Furthermore, increasing processing and collection capacities improves economic outcomes while simultaneously strengthening agility and resilience. A higher proportion of recyclable products substantially enhances value recovery and service levels, albeit with implications for node criticality.

Keywords: Reverse Logistics; Agri-food Reverse Logistics Industry; Agility; Resilience; Circular Economy.

1. Introduction

The sharp rise in the global population over recent decades has intensified pressure on food production systems, resulting in a marked increase in food demand worldwide. As a consequence, food waste has emerged as a critical concern within the food industry and agricultural supply chains (Sharifi et al., 2023). Recent estimates indicate that nearly one-third of total food production is ultimately discarded, representing a massive loss of valuable resources and creating serious long-term environmental and economic implications (Krishnan et al., 2022), addressing this challenge requires the adoption of systematic and sustainable approaches, among which the development of effective reverse logistics structures in the agricultural industry plays a pivotal role. Reverse logistics facilitates the coordinated handling of surplus, returned, and waste food products, aiming to significantly reduce waste generation while improving resource utilization and recovery (Mallick et al., 2024). In the agri-food industry, apples play a vital role in the global food chain due to their high consumption rate, long storage life, and wide use in both fresh and processed food products. They contribute significantly to food security, agricultural income, and the agri-processing industry. However, a considerable amount of apples is lost or downgraded during harvesting, storage, and distribution. In this context, reverse logistics is essential for efficiently managing apple waste and by-products. Through reverse logistics, damaged or surplus apples can be redirected to alternative uses such as juice production, animal feed, composting, or bioenergy generation. This not only reduces food waste but also enhances resource efficiency and supports sustainable and circular food systems. Agility is the capability of a system to quickly sense, respond to, and adapt to unexpected changes and uncertainties in its operating environment (Alamroshan et al., 2022). In the context of reverse logistics, agility is particularly important due to the variability in the quantity, quality, and timing of returned or waste products. An agile reverse logistics system enables organizations to rapidly adjust collection, sorting, processing, and redistribution activities in response to fluctuations in returns, demand, and regulatory requirements. By enhancing responsiveness and flexibility, agility helps reduce operational delays, minimize costs, improve resource recovery, and ultimately enhance the overall effectiveness and sustainability of reverse logistics networks (Zeynali et al., 2025). On the other hand, resilience refers to the ability of a system to withstand disruptions, recover quickly, and maintain or restore its core functions under uncertain and adverse conditions (Namdar et al., 2021; Abdelaziz et al., 2026). In reverse logistics, resilience is especially critical because return flows are often unpredictable and highly sensitive to external shocks such as demand fluctuations, transportation disruptions, regulatory changes, or environmental events. A resilient reverse logistics system can absorb disturbances, reconfigure its processes, and continue operating with minimal performance loss (Zeynali et al., 2025).

Another concept that has drawn considerable attention from both researchers and practitioners in recent years is the circular economy. The circular economy is an economic paradigm that emphasizes closing material loops by reducing waste, reusing resources, and recycling by-products throughout the production and consumption cycle (Nayeri et al., 2025, 2026). In the agri-food industry, this concept is particularly important due to the high volume of organic waste and resource-intensive nature of food production. By adopting circular economy principles, agri-food systems can transform agricultural residues and food waste into valuable outputs such as animal feed, compost, bioenergy, or bio-based products. This approach reduces environmental impacts, improves resource efficiency, enhances food system sustainability, and supports long-term economic and ecological resilience.

Building on the significance of the above considerations, this study aims to develop an effective reverse logistics network for the agri-food industry by explicitly integrating circular economy principles alongside agility and resilience capabilities. To achieve this objective, a comprehensive multi-objective mathematical programming framework is developed to simultaneously optimize economic performance, agility, and resilience indicators while embedding circular resource flows into network decisions. Given the inherently high level of uncertainty in supply chain environments, the proposed problem is examined under mixed uncertainty conditions, which are addressed using a robust stochastic–possibilistic programming approach. Moreover, to derive a well-balanced and reliable solution, a recently developed goal programming technique, namely FMCCGP-UF is employed. The primary contribution of this study, in comparison with existing literature, lies in proposing a circular economy–driven reverse logistics network that systematically enhances both agility and resilience, with a specific application to the apple supply chain.

Despite the growing body of literature on agri-food reverse logistics, no previous study has specifically addressed the design of an apple reverse supply chain network that simultaneously integrates circular economy principles, agility, and resilience under mixed uncertainty. To fill this research gap, the present study pursues three primary objectives: (1) to develop a multi-echelon reverse logistics network for apple waste that enables value recovery through composting, bioenergy generation, and animal feed production; (2) to formulate a multi-objective mathematical programming model that maximizes economic performance, minimizes node criticality (as a resilience metric), and maximizes service levels (as an agility indicator); and (3) to solve the model using the FMCCGP-UF method under a robust stochastic-possibilistic framework. The specific goals are to identify optimal locations for collection and recycling centers, determine critical nodes over multiple periods, and evaluate the impact of processing capacities and recyclable product rates on network performance.

2. Literature Review

This section presents a review of the relevant literature, with particular emphasis on studies that have addressed the configuration of agri-food supply chains incorporating key features such as circular economy, agility, and resilience. In this way, Gupta et al. (2021) developed an agri-food supply chain network design for India that simultaneously addresses strategic and operational considerations. Their study proposed a fuzzy model aimed at minimizing costs while embedding sustainability objectives, reducing food losses, and enhancing system flexibility. In a related stream of research, Hasani et al. (2021)developed a decision framework for designing a green and resilient supply chain network. Their study introduced a robust optimization model that accounts for disruption scenarios while integrating economic and environmental considerations, along with mitigation strategies aimed at enhancing network flexibility. The model was solved using metaheuristic algorithms, and the results revealed that the significance of supply chain agility becomes more pronounced as budget uncertainty increases, while certain mitigation strategies may conflict with agile production principles. Joshi et al. (2023) conducted a study centered on sustainability in the agri-food supply chain. The study focused on determining the primary factors influencing the implementation of sustainable farming methods in India and explored the major obstacles encountered in operating a sustainable agricultural supply chain. The results indicated that limited capacity to implement sustainable practices and the absence of an integrated policy framework for sustainable agricultural businesses are the most critical barriers. The identified influencing factors can provide valuable guidance for policymakers and regulators in shaping effective strategies for sustainable agricultural development.

Sharma et al. (2023) proposed a framework for designing a blockchain-based agricultural food supply chain. Using expert survey data, they evaluated the effects of blockchain adoption on supply chain advancement and identified five critical improvement dimensions: traceability, transparency, information security, transactional efficiency, and trust and quality. Their findings emphasized that blockchain technology can strengthen data security, reduce transaction costs, and build trust among supply chain actors, enabling more direct interactions without reliance on intermediaries. Gholian-Jouybari et al. (2023) focused on developing a closed-loop supply chain for soy-based products under the circular economy framework. They proposed a model to evaluate supply chain performance while integrating circular economy and sustainability principles. The model simultaneously addresses objectives such as net profit, carbon emissions, and customer satisfaction, and it is solved using a hybrid approach that combines multi-objective optimization techniques with advanced algorithms. Belhadi et al. (2024) investigated how digital capabilities help manage uncertainty in agri-food supply chains. Research on established firms revealed that downstream players, including wholesalers and retailers in Africa's agri-food sector, make extensive use of digital technologies to gather and analyze data. These capabilities enable them to anticipate worst-case scenarios arising from geopolitical disruptions and take proactive measures to minimize potential negative impacts. Gholipour et al. (2024) proposed a multi-objective optimization model for a closed-loop pomegranate supply chain that combines artificial intelligence with reverse logistics to reduce food waste and improve farmers' incomes. In their approach, discarded pomegranates are transformed into value-added products, such as ethanol and compost. The model covers the entire supply chain, including producers, processing facilities, recycling centers, and end markets. Its main objectives are to minimize total costs and supply risk, with findings indicating that higher supply risk leads to increased costs and reduces the overall responsiveness of the supply chain network. Zeynali et al. (2025) proposed a hybrid decision-making framework to develop an agile and resilient reverse logistics network for the agricultural industry, using corn as a case study. Vamarzani et al. (2025) developed a multi-objective model to design a backward supply chain network for bananas. The model focuses on optimizing sustainability-related metrics, including total cost, greenhouse gas emissions, and employment opportunities. In the study by Sarkar et al. (2025), focusing on the agri-food supply chain, a framework is proposed to minimize food waste in developing countries, examining the issue from economic, environmental, social, and operational sustainability perspectives. The results indicate that factors such as strategic planning, logistics, inventory management, resilient infrastructure, technology planning, and digital transformation play the most significant roles in reducing waste in the food supply chain. Kayan et al. (2025) focused on bio-hydrogen production from agricultural waste is investigated as a strategy aligned with the circular economy and carbon neutrality. This research employs a digital twin framework to optimize logistics and supply chain management for bio-hydrogen production, utilizing Greenfield analysis, Monte Carlo simulation, and network optimization. Chaudhari et al. (2026) examined the drivers affecting the implementation of green supply chain management in agricultural equipment manufacturing industries. Using the TOPSIS multi-criteria decision-making method, this research prioritizes the key drivers of green supply chains and identifies Industry 4.0 technologies as the most important factor for developing green supply chains. Jauhari et al. (2026) developed an optimization model for designing a closed-loop supply chain in the corn industry that simultaneously considers waste recycling, job creation, and carbon emission control policies. The proposed model is designed with the objectives of minimizing operational costs and increasing employment opportunities. Cheraghalipour et al. (2025) designed an eight-level network for a closed-loop agricultural supply chain that incorporates recycling, biogas production, and composting within the network structure. To this end, a two-stage programming model is developed, where the upper level minimizes costs and the lower level maximizes the profit from selling biogas and compost. To solve the model, hybrid metaheuristic algorithms including genetic algorithm and random fractal search are employed. Fatorachian et al. (2025) investigated the role of digitalization in improving waste management efficiency and the sustainability of cold supply chains. Focusing on technologies such as artificial intelligence, the Internet of Things, and predictive analytics, this study evaluates the impact of digital solutions on waste reduction and carbon dioxide emissions. The results indicate that real-time monitoring, predictive maintenance, and enhanced information transparency play an effective role in reducing waste, improving energy efficiency, and promoting the sustainability of cold chains. Haider et al. (2025) examined the factors contributing to fruit and vegetable losses and waste in the supply chain with the aim of transitioning toward sustainable consumption and production patterns. Focusing on the agricultural supply chain from the farm stage to the retail level, this study provides a structural analysis of factors influencing food waste. To this end, a hybrid multi-criteria decision-making approach within a grey logic framework is employed to identify causal relationships among the factors and determine their weighting.

Despite the valuable contributions of the above studies, several limitations persist. First, most studies focus on a single or at most two performance dimensions (e.g., cost and sustainability), whereas the simultaneous integration of circular economy, agility, and resilience remains underexplored. Second, the majority of research has been conducted on cereals (wheat, corn, soybean), fruits (pomegranate, banana), or generic agri-food products, with no dedicated study on the apple reverse supply chain. Third, existing models often overlook mixed uncertainty (i.e., simultaneous epistemic and aleatory uncertainty) or rely solely on fuzzy or stochastic methods, not their combination. Fourth, the concept of node criticality as a proxy for resilience is novel and has not been applied in apple waste networks. To the best of our knowledge, no previous study has designed an apple reverse logistics network that explicitly integrates circular economy, agility, and resilience under mixed uncertainty using a robust stochastic-possibilistic approach with node criticality and service level metrics. This gap is particularly significant given the high production volume, perishability, and waste generation rates of apples, as well as the economic importance of apple-growing regions such as Mazandaran Province in Iran.

Overall, although numerous studies have addressed agri-food logistics network design, the configuration of an apple reverse supply chain network, particularly from the perspective of circular economy, agility, and resilience dimensions, has not yet been explored in the academic literature. To bridge this gap, the present study develops a multi-objective mathematical programming model for designing an apple reverse logistics network that explicitly incorporates the financial, circular economy, agility, and resilience aspects. To effectively address mixed uncertainty in the problem parameters, the stochastic–possibilistic programming approach is employed. In addition, a recently introduced solution framework, referred to as FMCCGP-UF, is employed to solve the resulting model efficiently. Overall, this research advances the literature by investigating the apple reverse supply chain network design problem under mixed uncertainty, considering circular economy, resilience, and agility principles.

3. Problem Definition

As noted earlier, this study aims to design the apple reverse supply chain network by incorporating agility and resilience dimensions. The proposed waste chain is structured into six echelons: apple farms as waste generation sources, collection centers (CCs), recycling centers (RCs), animal husbandry facilities (AH), energy demand points (DE), and compost demand points (DC), as illustrated in Figure 1. In this framework, waste generated at farms is first gathered by the collection centers, where it is inspected and sorted. The recyclable portion of the collected waste is then transported to recycling centers, while the remaining fraction is directed to animal husbandry. At the recycling stage, waste is processed into compost and energy; the compost output is delivered to DCs, and the energy output is supplied to DEs.

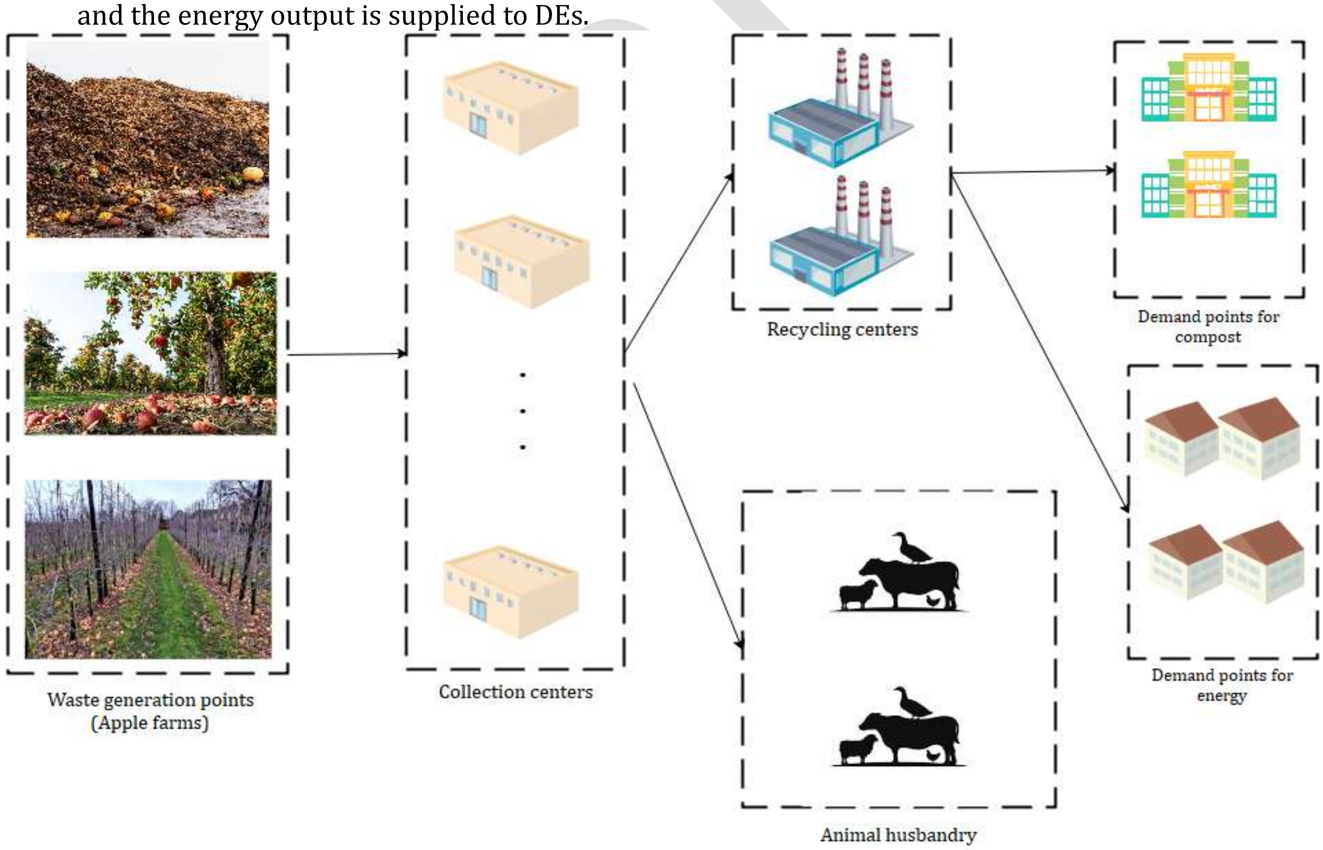

Figure 1. The considered supply chain

The following section introduces the notations used in the mathematical model.

Indices

f	Index of farms
i	index of CCs
r	index of RCs
j	Index of DCs
k	Index of DEs
q	Index of AHs
t	Index of periods
s	Index of scenarios

Parameters

$\widetilde{IAW}_{fts}$	The amount of waste generated at farm f during period t under scenario s
$\widetilde{CoC}_{ft}$	The cost of collecting waste from farm f during period t
$\widetilde{ECC}_{i}$	The cost required to establish collection center i
$\widetilde{ECR}_{r}$	The cost required to establish recycling center r
$\widetilde{RO}_{rt}$	The operational cost in RC r in period t
$\widetilde{CoS}_{jt}$	The cost incurred due to compost shortage at DC j during period t
$\widetilde{CoE}_{kt}$	The cost incurred due to energy shortage in DE k in period t
$\widetilde{CoQ}_{qt}$	The cost incurred due to the shortage in AH q in period t
$\widetilde{TC}_{t}$	The unit of transportation cost in period t
$\widetilde{ESP}_{kt}$	The selling price of energy in DE k
$\widetilde{CSP}_{jt}$	The selling price of compost in DC j
$\widetilde{ASP}_{qt}$	The selling price of collected waste in AH q
$CapR_{r}$	The capacity of RC r
$CapC_{i}$	The capacity of CC c
$\widetilde{DemA}_{qts}$	The demand for fodder in AH q under scenario s
$\widetilde{DemC}_{jts}$	The demand for compost in DC j under scenario s
$\widetilde{DemE}_{kts}$	The demand for energy in DE k under scenario s
$Dis_{ff'}$	The distance separating centers f and f',(f and $f' \in \{f, i, j, r, k\}$)
μ_{t}	The proportion of collected waste that can be recycled in period t
ρ_{t}	The conversion rate of collected waste into compost during period
β_{t}	The conversion rate of collected waste into energy during period t.
$\widetilde{UC}_{ct}$	The node criticality threshold for RC r in period t
$\widetilde{UR}_{rt}$	The node criticality threshold for CC c in period t
$BigM$	A large positive number

Decision variables

BC_{jts}	The unmet demand at point d during period t for scenario s
BE_{kts}	The unmet demand at point e during period t for scenario s
BA_{qts}	The unmet demand at point q during period t for scenario s
QCA_{iqts}	The quantity of collected waste transported from collection center i to another node q during period t under scenario s.
WRE_{rkts}	The quantity of energy transported from recycling center r to DE unit k during period t under scenario s.
WCR_{irts}	The quantity of collected waste transported from collection center i to recycling center r during period t under scenario s.
WRC_{rjts}	The quantity of compost transported from recycling center r to DC j during period t under scenario s.
WFC_{fits}	The quantity of waste collected from farm f and shipped to collection center i during period t under scenario s.
RR_{r}	1 if RC r is opened; 0 otherwise

CC_i	1 if CC i is opened; 0 otherwise
RCI_{rt}	1 if RC r is a critical node in period t; 0 otherwise
CCI_{it}	1 if CC i is a critical node in period t; 0 otherwise
$\alpha 1$	Service level for animal husbandry units (AHs); continuous decision variable, $0 \leq \alpha_1 \leq 1$
$\alpha 2$	Service level for compost demand points (DCs); continuous decision variable, $0 \leq \alpha_2 \leq 1$
$\alpha 3$	Service level for energy demand points (DEs); continuous decision variable, $0 \leq \alpha_3 \leq 1$

Using the notations and definitions introduced above, the mathematical model for the research problem is formulated as follows.

$$\begin{aligned} Max\ Z1 = &\left(\sum_s PS_s \left(\sum_r \sum_j \sum_t \widetilde{CSP}_{jt}.WRC_{rjts} + \sum_r \sum_k \sum_t \widetilde{ESP}_{kt}.WRE_{rkts} \right.\right.\\ &\left.\left. + \sum_i \sum_q \sum_t \widetilde{ASP}_{qt}.QCA_{iqts}\right)\right)\\ &-\left(\sum_r \widetilde{ECR}_r.RR_r + \sum_i \widetilde{ECC}_i.CC_i\right.\\ &+ \sum_s PS_s \left(\sum_i \sum_f \sum_t \widetilde{CoC}_{ft}.WFC_{fits}\right.\\ &+ \sum_i \sum_r \sum_t \sum_k \widetilde{RO}_{rt}.(WCR_{irts} + WRE_{rkts}) + \sum_q \sum_t \widetilde{CoQ}_{qt}.BA_{qts}\\ &+ \sum_k \sum_t \widetilde{CoE}_{kt}.BE_{kts} + \sum_j \sum_t \widetilde{CoS}_{jt}.BC_{jts}\\ &+ \sum_t TC_t.\left(\sum_f \sum_i Dis_{fi}.WFC_{fits} + \sum_r \sum_k Dis_{rk}.WRE_{rkts}\right.\\ &\left.\left.\left. + \sum_i \sum_q Dis_{iq}.QCA_{iqts} + \sum_i \sum_r Dis_{ir}.WCR_{irts} + \sum_j \sum_r Dis_{rj}.WRC_{rjts}\right)\right)\right) \end{aligned} \tag{1}$$

$$Min\ Z2 = \sum_r \sum_t RCI_{rt} + \sum_i \sum_t CCI_{it} \tag{2}$$

$$Max\ Z3 = \alpha 1 + \alpha 2 + \alpha 3 \tag{3}$$

$$\sum_i WFC_{fits} \leq \widetilde{IAW}_{fts} \qquad \forall f,t,s \tag{4}$$

$$\sum_r WCR_{irts} = \sum_f \mu_t.WFC_{fits} \qquad \forall i,t,s \tag{5}$$

$$\sum_q QCA_{iqts} = \sum_f (1-\mu_t).WFC_{fits} \qquad \forall i,t,s \tag{6}$$

$$\sum_i QCA_{iqts} + BA_{qts} = \widetilde{DemA}_{qts} \qquad \forall q,t,s \tag{7}$$

$$\sum_j WRC_{rjts} = \sum_i \rho_t.WCR_{irts} \qquad \forall r,t,s \tag{8}$$

$$\sum_{r} WRC_{rjts} + BC_{jts} = \widetilde{DemC}_{jts} \qquad \forall j,t,s \qquad (9)$$
$$\sum_{k} WRE_{rkts} = \sum_{i} \beta_t . WCR_{irts} \qquad \forall r,t,s \qquad (10)$$
$$\sum_{r} WRE_{rkts} + BE_{kts} = \widetilde{DemE}_{kts} \qquad \forall k,t,s \qquad (11)$$
$$\sum_{r} WCR_{irts} + \sum_{q} QCA_{iqts} \le CapC_i . CC_i \qquad \forall i,t,s \qquad (12)$$
$$\sum_{j} WRC_{rjts} + \sum_{k} WRE_{rkts} \le CapR_r . RR_r \qquad \forall r,t,s \qquad (13)$$
$$\frac{\sum_i \sum_q \sum_t \sum_s QCA_{iqts}}{\sum_q \sum_t \sum_s \widetilde{DemA}_{qts}} \le \alpha 1 \qquad (14)$$
$$\frac{\sum_r \sum_j \sum_t \sum_s WRC_{rjts}}{\sum_j \sum_t \sum_s \widetilde{DemC}_{jts}} \le \alpha 2 \qquad (15)$$
$$\frac{\sum_r \sum_k \sum_t \sum_s WRE_{rkts}}{\sum_{jk} \sum_t \sum_s \widetilde{DemE}_{kts}} \le \alpha 3 \qquad (16)$$
$$\sum_{f} WFC_{fits} + \sum_{r} WCR_{irts} + \sum_{q} QCA_{iqts} \le BigM . CCI_{it} + UC_{it} \qquad \forall i,t,s \qquad (17)$$
$$\sum_{f} WFC_{fits} + \sum_{r} WCR_{irts} + \sum_{q} QCA_{iqts} > CCI_{it} . UC_{it} \qquad \forall i,t,s \qquad (18)$$
$$\sum_{i} WCR_{irts} + \sum_{j} WRC_{rjts} + \sum_{j} WRE_{rkts} \le BigM . RCI_{rt} + UR_{rt} \qquad \forall r,t,s \qquad (19)$$
$$\sum_{i} WCR_{irts} + \sum_{j} WRC_{rjts} + \sum_{j} WRE_{rkts} > RCI_{rt} . UR_{rt} \qquad \forall r,t,s \qquad (20)$$
$$RR_r, CC_i, RCI_{rt}, CCI_{it} \in \{0,1\}; \\ WFC_{fits}, WCR_{irts}, WRC_{rjts}, WRE_{rkts}, QCA_{iqts}, BA_{qts}, BE_{kts}, BC_{jts} \ge 0 \qquad (21)$$

Equation (1) is designed to maximize the total profit of the waste management network, whereas Equation (2) focuses on minimizing the number of critical nodes. Equation (3) aims to maximize the overall service level of the supply chain. Constraint (4) specifies the quantity of waste transported from farms to CCs, while Constraint (5) governs the amount of waste moved from CCs to RCs. Constraints (6) and (7) calculate the waste sent from CCs to AHs and the associated shortages. Similarly, Equations (8) and (9) evaluate the quantity of compost delivered from RCs to DC and the corresponding shortages. Relations (10) and (11) determine the energy transported from RCs to DEs and their shortages. Capacity limitations for CCs and RCs are expressed in Equations (12) and (13), respectively. Constraints (14)–(16) define the service levels (α_1, α_2, α_3) as decision variables. Each service level is computed as one minus the ratio of total unmet demand to total demand for the respective customer category. These variables are then maximized in the third objective function (Z_3), which serves as a proxy for agility. A higher service level indicates a more responsive and agile reverse logistics network, as it reflects the system's ability to satisfy customer demands despite uncertainties in waste supply, processing, and distribution. Also, Constraints (17) to (20) define the limitations related to node criticality within the network. In this context, UC_{it} and UR_{rt} represent the critical thresholds for nodes i and r, respectively. These constraints ensure that the quantity of goods dispatched from each node does not exceed its specified critical capacity, thereby maintaining the stability and reliability of the network. Finally, Constraint (21) defines the feasible ranges of the decision variables.

4. Uncertainty Modelling

Given the high degree of uncertainty in the supply chain management problem, this study examines the research problem under a mixed uncertainty setting. Accordingly, and in line with prior studies, a fuzzy–scenario framework is adopted to capture both vagueness and scenario-based variability in the model parameters (Fazli-Khalaf et al., 2017; Nayeri et al., 2021). In this way, to deal with the mentioned issue, this research uses an efficient method namely robust stochastic-possibilistic optimization approach. This method is a widely recognized strategy for handling various types of uncertainty and has been applied in numerous previous studies. To illustrate its application, a brief formulation is presented in Model (22), where y_s represents the control variable, x denotes the design variable, L, A, and h correspond to the constraint coefficients, and p_s indicates the probability assigned to each scenario.

$$\begin{aligned}
&Min\ Z = \tilde{g}\,x + \sum_{s} p_s\,\tilde{u}\,y_s \\
&\text{subject to} \\
&Ax \le \tilde{d}, \\
&Ly_s \ge \tilde{h}_s, \\
&x, y_s \ge 0.
\end{aligned} \tag{22}$$

Building on prior studies, the robust counterpart of Model (22) is presented as Model (23). In this formulation, $\tau$and ϑ represent the satisfaction levels, δ denotes the weight assigned to feasibility robustness, and β indicates the weight for optimality robustness. For a more detailed explanation of the methodology and practical examples, readers may consult (Fazli-Khalaf et al., 2017; Mamashli et al., 2021; Nayeri et al., 2021)

$$\begin{aligned}
&Min\ Z = \left[\frac{g^1+g^2+g^3}{3}\right] x + \sum_{s} p_s \left[\frac{u^1+u^2+u^3}{3}\right] y_s \\
&\qquad - \beta \sum_{s} p_s \left[\left(\left[\frac{u^1+u^2+u^3}{3}\right] y_s - \sum_{s'} p_{s'} \left[\frac{u^1+u^2+u^3}{3}\right] y_{s'}\right) + 2\theta_s\right] \\
&\qquad - \sum_{s} \varphi\,\psi_s \\
&Ax \le (2\tau-1)d^1 + (2-2\tau)\,d^2, \\
&Ly_s + \psi_s \ge (2-2\vartheta){h_s}^3 + \ (2\vartheta-1)\,{h_s}^2, \\
&\left[\frac{u^1+u^2+u^3}{3}\right] y_s - \sum_{s} p_s \left[\frac{u^1+u^2+u^3}{3}\right] y_s + \theta_s \ge 0.
\end{aligned} \tag{23}$$

5. Solution Approach

In this study, one of the recently developed variants of goal programming, called FMCCGP-UF, introduced by Sojoudi et al. (2025), was applied. This method was chosen due to several key advantages: (1) the ability to incorporate multiple aspiration levels, (2) explicit integration of decision makers' value judgments, (3) the use of a linear utility function, (4) simultaneous consideration of efficiency and equity in goal achievement, and (5) increased flexibility in modeling Sojoudi et al. (2025). The mathematical representation of FMCCGP-UF is given in Model (24). Here, $f_k(X)$ denotes the k-th objective function, and y_k is a continuous decision variable. The variables $d_k^+$and d_k^-indicate the positive and negative deviations of $f_k(X)$ from y_k, respectively. Furthermore, $U_{k,\max}$ and $U_{k,\min}$ define the upper and lower bounds of the aspiration level for the k-th objective. In this formulation, ξ_k^- represents the normalized deviation of y_k from $U_{k,\min}$, D is the maximum deviation value, λ_k denotes the achievement level of the k-th objective, and MED_k corresponds to the maximum expected deviation for that objective.

$$
\begin{aligned}
& Max = \sum_k \lambda_k - \sum_k w_k^{\xi}.\xi_k^- \\
& s.t. \\
& \lambda_k \leq 1 - \frac{\tau.D + (1-\tau).\left(w_k^d.(d_k^+ + d_k^-)\right)}{MED_k} && \forall k \\
& f_k(X) + d_k^- - d_k^+ = y_k && \forall k \\
& w_k^d.(d_k^+ + d_k^-) + w_k^d.\xi_k^- \leq D && \forall k \\
& \phi_k \leq \frac{U_{k,max} - y_k}{U_{k,max} - U_{k,min}} \text{ for the minmimization} \\
& && \forall k \\
& \phi_k \leq \frac{y_k - U_{k,min}}{U_{k,max} - U_{k,min}} \text{ for the maximization} \\
& U_{kmin} \leq y_k \leq U_{kmax} && \forall k \\
& \phi_k + \xi_k^- = 1 && \forall k \\
& d_k^+, d_k^-, y_k, U_k, \xi_k^- \geq 0 && \forall k
\end{aligned}
\tag{24}
$$

The final model (the FMCCGP-UF counterpart for the original model) is presented in Model (25).

$$
\begin{aligned}
& Max = \lambda_1 + \lambda_2 + \lambda_3 - w_1^{\xi}.\xi_1^- - w_2^{\xi}.\xi_2^- - w_3^{\xi}.\xi_3^- \\
& s.t. \\
& \lambda_1 \leq 1 - \frac{\tau.D + (1-\tau).(w_1^d.(d_1^+ + d_1^-))}{MED_1} \\
& \lambda_2 \leq 1 - \frac{\tau.D + (1-\tau).(w_2^d.(d_2^+ + d_2^-))}{MED_2} \\
& \lambda_3 \leq 1 - \frac{\tau.D + (1-\tau).(w_3^d.(d_3^+ + d_3^-))}{MED_3} \\
& f_1(X) + d_1^- - d_1^+ = y_1 \\
& f_2(X) + d_2^- - d_2^+ = y_2 \\
& f_3(X) + d_3^- - d_3^+ = y_3 \\
& w_1^d.(d_1^+ + d_1^-) + w_1^d.\xi_1^- \leq D \\
& w_2^d.(d_2^+ + d_2^-) + w_2^d.\xi_2^- \leq D \\
& w_3^d.(d_3^+ + d_3^-) + w_3^d.\xi_3^- \leq D \\
& \phi_1 \leq \frac{y_1 - U_{1,min}}{U_{1,max} - U_{1,min}} \\
& \phi_2 \leq \frac{U_{2,max} - y_2}{U_{2,max} - U_{2,min}} \\
& \phi_3 \leq \frac{y_3 - U_{3,min}}{U_{3,max} - U_{3,min}} \\
& U_{1,min} \leq y_1 \leq U_{1,max} \\
& U_{2,min} \leq y_2 \leq U_{2,max} \\
& U_{3,min} \leq y_3 \leq U_{3,max} \\
& \phi_1 + \xi_1^- = 1 \\
& \phi_2 + \xi_2^- = 1 \\
& \phi_3 + \xi_3^- = 1 \\
& Model's\ constraints
\end{aligned}
\tag{25}
$$

6. Numerical Results

6.1. Case Study and Input Data

As aforementioned, this work focused on the agri-food industry. In this regard, the agri-food industry is a cornerstone of economic development, food security, and societal well-being, encompassing the production, processing, distribution, and consumption of agricultural products. With increasing population growth, urbanization, and changing consumer preferences, the demand for high-quality, safe, and sustainably produced food continues to rise. Efficient management of agri-food supply chains enhances product quality, reduces waste, and improves profitability for stakeholders.

Moreover, the integration of circular economy principles and sustainable practices strengthens environmental conservation, resource efficiency, and resilience against disruptions such as climate change, pandemics, and market fluctuations. These factors underscore the strategic importance of research focused on improving sustainability, efficiency, and adaptability within the agri-food sector. Among agricultural products, apples hold a unique position due to their high nutritional value, widespread consumption, and economic significance. Their perishable nature, seasonal production, and susceptibility to damage during handling and transportation present notable supply chain challenges. Reverse logistics, covering the collection, recycling, and disposal of surplus or damaged apples, plays a crucial role in mitigating waste and enhancing sustainability. Beyond environmental benefits, effective reverse logistics allows value recovery through processing into juices, jams, or animal feed, thereby improving economic efficiency. Optimizing apple reverse supply chains also promotes circular economy principles and aligns with growing consumer expectations for responsible and sustainable food production. Mazandaran province, situated along the southern coast of the Caspian Sea in northern Iran, is one of the country's most fertile and agriculturally productive regions. Its temperate climate, abundant rainfall, and fertile soils support diverse crop cultivation, with apples representing a major economic and cultural product. The apple industry contributes significantly to local income, employment, and trade, supplying both domestic markets and international exports. However, the perishable nature of apples and the seasonal fluctuations in production necessitate effective supply chain and reverse logistics strategies to minimize post-harvest losses, manage damaged or surplus fruits, and maintain product quality. Studying apple reverse logistics in Mazandaran provides valuable insights for designing sustainable, resilient, and economically efficient agri-food systems, supporting both regional economic development and environmental stewardship. The values of some key parameters of the proposed model are presented in Tables 1& 2, based on information from the literature and expert opinions. The study considers three distinct scenarios for the problem: optimistic ($PS_1 = 0.25$), most-likely ($PS_2 = 0.5$), and pessimistic ($PS_3 = 0.25$).

Table 1. The values of the fuzzy parameters

Parameter	$Value$			
	α_1	α_2	α_3	α_4
$\widetilde{ECC}_i$ (Million Toman)	$U[100\ 150]$	$U[150\ 200]$	$U[200\ 250]$	$U[250\ 300]$
$\widetilde{ECR}_r$ (Million Toman)	$U[350\ 400]$	$U[400\ 450]$	$U[450\ 500]$	$U[500\ 550]$
$\widetilde{CoC}_{ft}$ (Toman)	$U[50\ 100]$	$U[150\ 200]$	$U[250\ 300]$	$U[300\ 350]$
$\widetilde{TC}_t$ ((Toman /Ton − Km))	$U[0.115\ 0.120]$	$U[0.020\ 0.125]$	$U[0.125\ 0.130]$	$U[0.130\ 0.135]$

Table 2. The values of other parameters

Parameter	$Value$
μ_t	$U[0.6\ 0.8]$
ρ_t	$U[0.4\ 0.6]$
β_t	$U[0.4\ 0.6]$

6.2. Computational Results

This section reports the results obtained from solving the proposed multi-objective model using the FMCCGP-UF approach. To account for uncertainty, three scenarios are examined: pessimistic ($P_1 = 0.25$), most-likely ($P_2 = 0.50$), and optimistic ($P_3 = 0.25$). Accordingly, the lower and upper bounds of the aspiration levels, $U_{k,\min}$ and $U_{k,\max}$, for each objective function u are summarized in Table 3. The final optimization results are provided in Table 4. Based on the obtained results, value of Z1, Z2, and Z3 are respectively equal to 308495360.2, 7, and 2.2. Also, the outcomes show that recycling centers #2 and #5 are established. Moreover, results demonstrate that collection centers #1, #3, and #4 are opened. Furthermore, based on the achieved outputs, recycling center #2 in periods #2 and #5 are a critical node. Additionally, outcomes show that collection center #1 in periods #3 and #5, and collection center #2 in periods #1 and #5 are a critical node. Furthermore, according to the results, service level for AHs, DCs, and Des are respectively equal to 0.73, 0.78, and 0.69. It should be noted that the model includes numerous continuous flow variables, each indexed by period t and scenario s. Reporting the numerical value of every continuous variable would require dozens of pages, which is not feasible due to journal page limits. Moreover, individual variable values are rarely informative for practitioners. Instead, the following key performance indicators and trends derived from these variables are presented and analyzed.

Table 3. Values of the aspiration levels for each objective function

Objective function	Aspiration level	Value
$Z1$	$U_{k,min}$	90426128.1
	$U_{k,max}$	352817650.8
$Z2$	$U_{k,min}$	0
	$U_{k,max}$	21
$Z3$	$U_{k,min}$	0
	$U_{k,max}$	2.7

Table 4. The results of solving the proposed model

Variable	Value
$Z1$	308495360.2
$Z2$	7
$Z3$	2.2
RR_2	1
RR_5	1
CC_1	1
CC_3	1
CC_4	1
RCI_{22}	1
RCI_{25}	1
CCI_{13}	1
CCI_{14}	1
CCI_{21}	1
CCI_{25}	1
$\alpha 1$	0.73
$\alpha 2$	0.78
$\alpha 3$	0.69

6.3. Sensitivity Analysis

6.3.1. Capacity

Since capacity is a critical parameter in the proposed model, this section performs a sensitivity analysis to examine its influence on the model outcomes. To this end, the model is solved under different capacity levels. Figure 2 illustrates the results of the sensitivity analysis for the first objective function. As shown in Figure 2, increasing capacity leads to a monotonic improvement in Z_1. A 30% increase in capacity yields a 24.6% improvement in economic performance compared to the base case. Conversely, a 30% capacity reduction results in a 31.2% decline in Z_1. This asymmetric effect indicates that under-capacity is more detrimental than over-capacity, which is particularly relevant for investment decisions. The underlying reason is that higher capacity enables greater throughput of recyclable waste, leading to higher revenues from compost, energy, and animal feed sales, while also reducing unmet demand penalties. Figure 3 presents the variation of the second and third objective functions with respect to changes in the capacity parameter. Figure 3 (left axis) shows that Z_2 decreases as capacity increases. Specifically, a 30% capacity increase reduces node criticality from 7 to 4 (a 42.9% improvement), while a 30% capacity reduction increases Z_2 to 12 (a 71.4% deterioration). This finding confirms that capacity expansions effectively "de-congest" critical nodes, distributing flows across multiple facilities and reducing the risk of disruption propagation. Notably, the relationship is nonlinear: beyond +20% capacity, the marginal reduction in Z_2 diminishes, suggesting a saturation effect. As shown in Figure 3 (right axis), service levels (Z_3) improve with capacity increases. A 30% capacity increase raises Z_3 from 2.2 to 3.4 (a 54.5% improvement). The most significant gains occur for energy demand points (α_3 increases from 0.69 to 0.89), followed by compost (α_2 from 0.78 to 0.91) and animal feed (α_1 from 0.73 to 0.88). This indicates that energy conversion processes are the most capacity-constrained and therefore benefit the most from expansion. The results suggest that capacity planning should prioritize recycling centers over collection centers, as recycling bottlenecks have a larger impact on service levels and node criticality. A pragmatic strategy is to design facilities with modular expansion capability, allowing incremental capacity increases based on observed waste volumes.

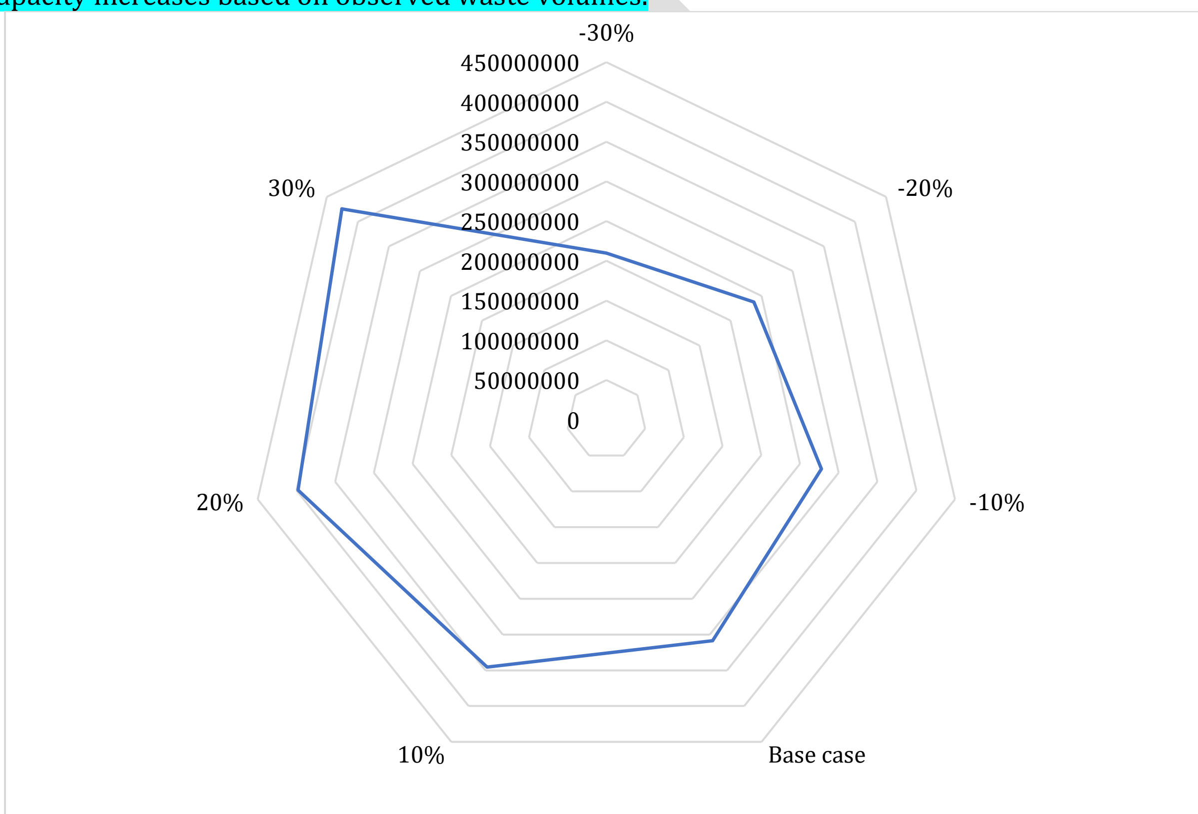

Figure 2. Impact of the capacity parameter on Z_1

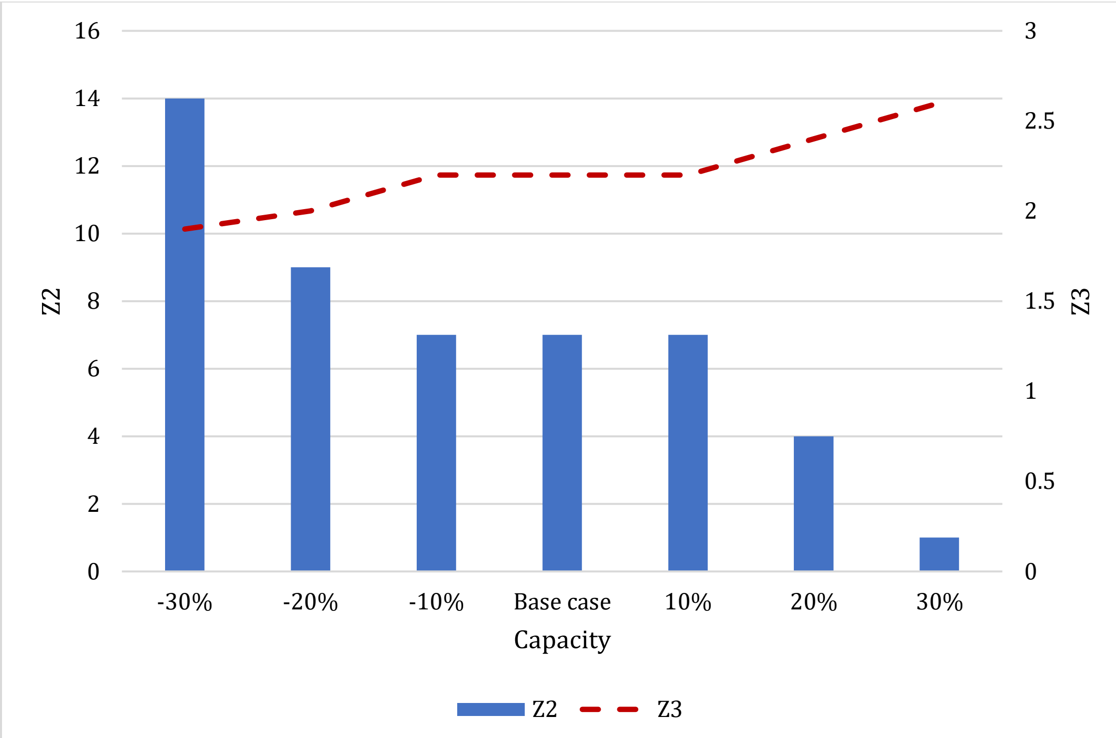

Figure 3. Impact of the capacity parameter on Z_2 and Z_3

6.3.2. Rate of recyclable product

The parameter μ_t represents the proportion of collected apple waste that can be recycled (i.e., diverted from landfill or animal feed to recycling centers for compost and energy production). This parameter is influenced by factors such as on-farm sorting practices, post-harvest handling, storage conditions, and quality control at collection centers. To assess its impact, we solved the model for μ_t values ranging from 0.4 to 0.9. The results are presented in Figures 4 and 5.

Figure 4 demonstrates a strong positive correlation between μ_t and Z_1. Increasing μ_t from 0.5 to 0.8 (a 60% increase) improves Z_1 by 41.3% (from 218 million to 308 million Toman). Beyond $\mu_t = 0.8$, the marginal benefit decreases due to capacity constraints at recycling centers. This finding underscores that even modest improvements in waste segregation and quality control at the farm level can generate substantial economic returns. For example, training farmers on proper storage and sorting techniques (an estimated investment of 5–10 million Toman per season) can increase μ_t by 0.05–0.10, yielding an additional 15–30 million Toman in recovered value. As shown in Figure 5 (left axis), Z_2 increases with μ_t. A rise from $\mu_t = 0.5$ to $\mu_t = 0.85$ increases Z_2 from 3 to 9 (a 200% increase). This seemingly negative outcome occurs because a higher recyclable proportion directs more waste volume to recycling centers, potentially overloading them and creating critical nodes. However, this trade-off is acceptable if accompanied by capacity expansions (as analyzed in Section 6.3.1). The optimal operating region appears to be μ_t between 0.70 and 0.75, where Z_1 is reasonably high (~280 million) while Z_2 remains moderate (5–6 critical nodes). Figure 5 (right axis) shows that service levels improve monotonically with μ_t. Increasing μ_t from 0.5 to 0.85 raises Z_3 from 1.5 to 2.9 (a 93.3% improvement). The compost service level (α_2) benefits the most (from 0.62 to 0.88), followed by energy (α_3 from 0.55 to 0.79) and animal feed (α_1 from 0.68 to 0.85). Interestingly, animal feed service levels show the smallest improvement because feed can still be produced from non-recyclable waste, whereas compost and energy rely entirely on recyclable inputs.

Investing in technologies and practices that increase recyclability (e.g., better sorting equipment at collection centers, cold storage to preserve apple quality, and farmer training programs) yields high returns. However, managers must simultaneously plan for capacity adjustments to avoid excessive node criticality. A balanced strategy is to target μ_t = 0.70–0.75 while increasing recycling center capacity by 15–20%, which achieves 85–90% of the maximum possible Z_1 with only 40–50% of the maximum Z_2 penalty.

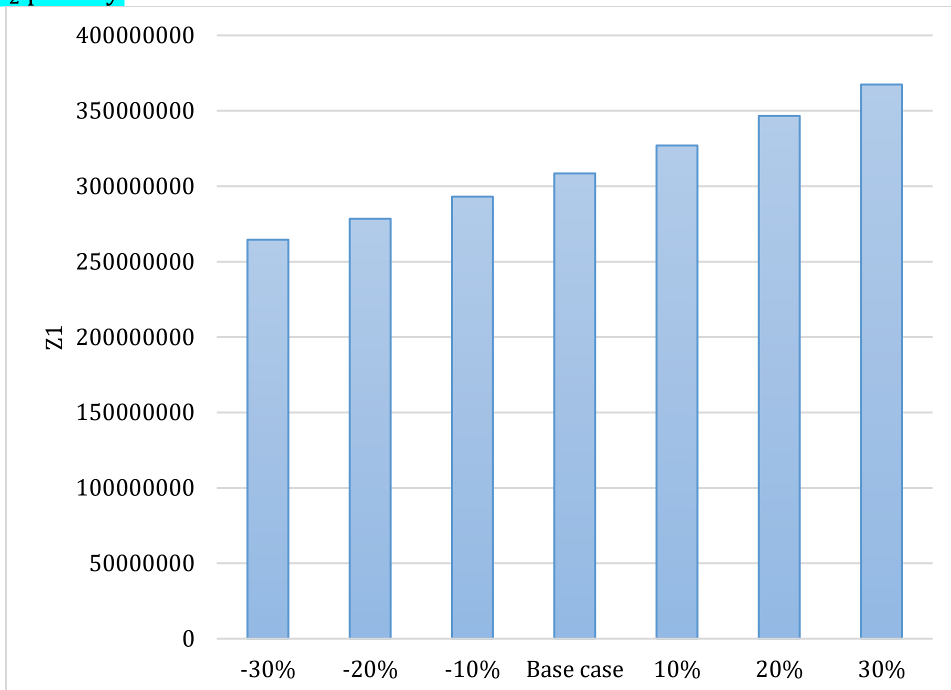

Figure 4. Impact of the μ_t on Z_1

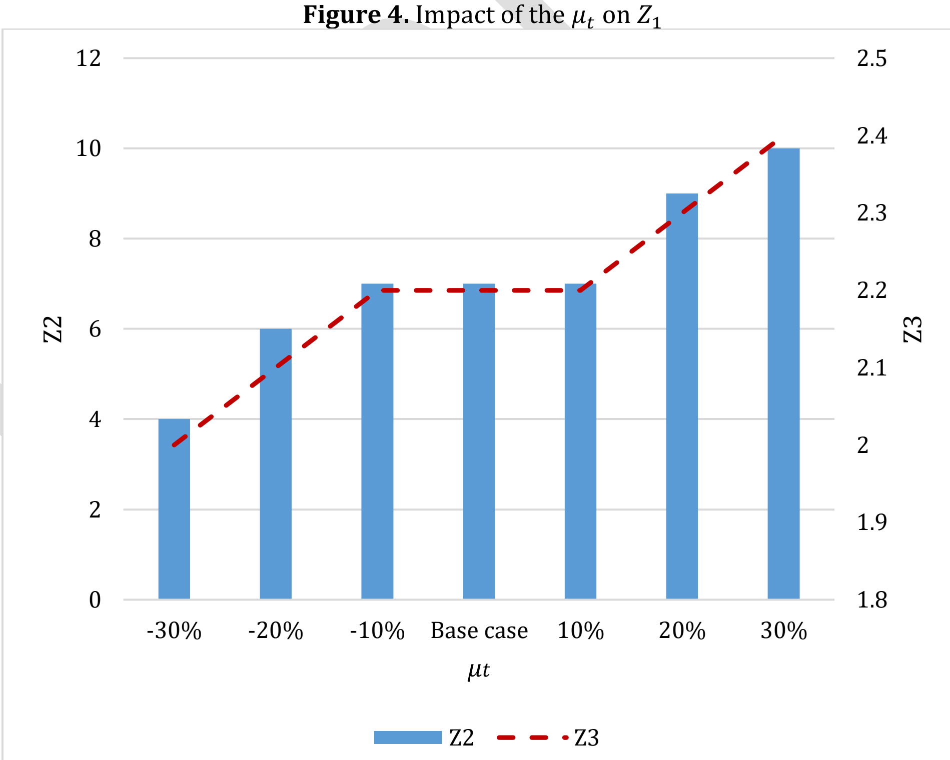

Figure 5. Impact of the μ_t on Z_2 and Z_3

6.4. Managerial Insights

The results of this study provide several actionable insights for managers and policymakers involved in agri-food and apple supply chains. First, the findings highlight that investing in well-located collection and recycling centers is a key managerial lever for simultaneously improving profitability, service level, and network stability. The identification of critical nodes over specific periods indicates that managers should not only focus on opening facilities but also actively monitor their operational load over time. Proactive capacity planning, temporary capacity expansion, or contingency contracts for transportation and processing during peak periods can substantially reduce the risk of node criticality. Moreover, the positive impact of higher recycling rates on economic performance and service levels suggests that managers should invest in better sorting technologies, farmer training, and quality control at the farm and collection stages to increase the proportion of recyclable apples and enhance value recovery. From a strategic perspective, the integration of circular economy principles with agility and resilience offers a practical roadmap for long-term sustainability. The results show that higher capacities and improved recycling ratios enhance responsiveness and reduce vulnerability to disruptions, which is particularly relevant in regions with seasonal production and demand uncertainty, such as Mazandaran province. Managers are therefore encouraged to adopt flexible contracts, multi-period planning, and scenario-based decision-making tools similar to the proposed model to balance cost efficiency with robustness under uncertainty. In addition, policymakers can use these insights to design incentive schemes, such as subsidies for recycling infrastructure or support for energy and compost markets, to strengthen circular flows. Overall, aligning operational decisions with circular, agile, and resilient strategies enables agri-food organizations to reduce waste, stabilize performance under uncertainty, and create sustainable economic and environmental value.

Based on the sensitivity analyses in Sections 6.3.1 and 6.3.2, additional insights emerge. The capacity analysis reveals that a 30% increase in processing capacity improves economic performance (Z_1) by 24.6% while reducing node criticality (Z_2) by 42.9%, indicating that capacity expansion is a dual-benefit strategy for both profitability and resilience. However, the marginal benefit diminishes beyond +20% capacity, suggesting that managers should avoid over-investment and instead adopt modular expansion in 10–15% increments. Furthermore, the recyclability analysis shows that increasing the proportion of recyclable waste (μ_t) from 0.5 to 0.8 improves Z_1 by 41.3% but increases Z_2 by 200%. This trade-off implies that pursuing maximum recyclability is not optimal; the recommended target is μ_t = 0.70–0.75, accompanied by a 15–20% capacity increase to mitigate criticality risks. Finally, energy recovery service levels (α_3 = 0.69) are the most capacity-constrained and benefit most from investment, suggesting that managers should prioritize energy conversion technologies when allocating limited budgets.

7. Conclusions and Future Directions

7.1. Summary of Key Findings

This research introduced a circular economy-based reverse logistics network for the apple agri-food supply chain that explicitly integrates agility and resilience under mixed uncertainty. The proposed multi-echelon structure spans farms, collection centers, recycling centers, animal husbandry units, and compost and energy demand points. A multi-objective mathematical model was formulated to maximize economic performance (Z_1), minimize node criticality as a resilience proxy (Z_2), and maximize service levels as an agility indicator (Z_3). The robust stochastic-possibilistic approach was employed to handle uncertainty, and the FMCCGP-UF method was used to obtain balanced solutions. The model was validated through a real-world case study in Mazandaran Province, Iran.

The key quantitative findings are as follows:

- The optimized network yields Z_1 = 308,495,360.2 Toman, Z_2 = 7 critical nodes, and Z_3 = 2.2 (service levels: α_1 = 0.73 for animal feed, α_2 = 0.78 for compost, α_3 = 0.69 for energy).

- Recycling centers #2 and #5 and collection centers #1, #3, and #4 are established. Critical nodes include recycling center #2 (periods 2 and 5) and collection centers #1 (periods 3 and 5) and #2 (periods 1 and 5).
- Sensitivity analysis reveals that a 30% increase in processing capacity improves Z_1 by 24.6% and reduces Z_2 by 42.9%, while increasing the recyclable product rate (μ_t) from 0.5 to 0.8 improves Z_1 by 41.3% but increases Z_2 by 200%.
- The optimal trade-off occurs at +15% capacity and +0.10 μ_t, yielding Z_1 = 342 million Toman, Z_2 = 6, and Z_3 = 2.8.

7.2. Limitations of the Study

Despite its contributions, this study has several limitations that should be acknowledged. Some input parameters (e.g., waste generation rates, demands, costs) were estimated based on expert opinions and limited field data. Although the robust stochastic-possibilistic approach mitigates uncertainty, more precise data would improve model accuracy. The model is specifically designed for apples and does not consider multi-product waste streams (e.g., mixed fruits or vegetables). Extending the model to multiple products would require additional complexity. Facility opening decisions (CC_i and RR_r) are treated as static (once opened, remain open). In reality, temporary closures or seasonal facility operations may be more cost-effective. While economic performance, agility, and resilience are addressed, environmental metrics (e.g., carbon emissions, water footprint) and social metrics (e.g., job creation, farmer welfare) are not explicitly modeled. Due to page limitations, the full robust counterpart and FMCCGP-UF reformulation were not presented. For large-scale instances (e.g., >50 farms, >20 periods), computational time may become prohibitive without metaheuristic algorithms.

7.3. Practical Recommendations

Based on the findings, the following recommendations are offered for managers, policymakers, and practitioners:

For supply chain managers:

- Prioritize capacity expansion at recycling centers that exhibit recurrent criticality (e.g., RC #2 in periods 2 and 5). Modular capacity increases of 15–20% provide the best return on investment.
- Invest in sorting technologies and farmer training programs to increase the recyclable product rate (μ_t). A 0.10 increase in μ_t yields approximately 15–30 million Toman additional value per season.
- Implement seasonal contingency plans (e.g., temporary labor, outsourcing agreements) during peak waste generation periods (post-harvest) to mitigate node criticality.

For policymakers:

- Subsidize recycling infrastructure (e.g., tax breaks or low-interest loans for collection and recycling centers) to encourage private sector participation.
- Support energy and compost markets by guaranteeing minimum purchase prices or providing feed-in tariffs for bioenergy generated from apple waste.
- Mandate or incentivize on-farm waste sorting and cold storage to improve recyclability at the source.

For practitioners:

- Adopt a two-stage sorting system: preliminary on-farm sorting followed by NIR-based grading at collection centers. This can increase μ_t by 0.10–0.15 with a payback period of 2–3 seasons.
- Use scenario-based planning tools similar to the proposed model to evaluate trade-offs between capacity, recyclability, and criticality before making strategic investments.

7.4. Future Research Directions

Beyond the directions briefly mentioned in the original manuscript, future studies can explore the following. For large-scale instances, develop efficient metaheuristics (e.g., NSGA-III, MOPSO, or genetic algorithms) to solve the model more quickly, as exact solvers may face scalability issues. Incorporate environmental objectives (e.g., minimizing carbon emissions, water usage, or land footprint) and social objectives (e.g., maximizing employment or farmer income) into a full triple-bottom-line framework. Integrate digital technologies such as IoT for real-time waste tracking, blockchain for traceability, and AI for demand forecasting, aligning with Industry 5.0 and waste management 5.0 paradigms. Allow temporary facility openings or seasonal operations to better match capacity with periodic waste generation patterns.

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