Original Research

Designing a sustainable integrated production system model under uncertainty considering the discount in production outsourcing costs

Saeed Shahdoust[1]. Mohammad Fallah[1*]. Esmaeil Najafi[2]

Received: 22 Oct 2022/ Accepted: 25 Feb 2023/ Published online: 01 March 2023

[*]Corresponding Author, fallahm1343@gmail.com

1- Department of Industrial Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran
2 - Department of Industrial Engineering, Science and research Branch, Islamic Azad University, Tehran, Iran

Abstract

Sustainability in the integrated production system in supply chain networks has led to the creation of competitive advantage for companies. Therefore, companies should have proper management of their supply chain network to increase their market share. Therefore, companies with proper design of the integrated production system in the company can take steps to reduce the cost and also reduce the amount of pollution by properly planning production or outsourcing production. Therefore, in this paper, a bi-objective model of a sustainable integrated production system is presented, taking into account the simultaneous reduction of possible costs on the system, the amount of greenhouse gas emissions, and the application of discounts on the costs of outsourcing production under uncertainty and the control of parameters with the robust-fuzzy-probabilistic optimization method. The main goal in this problem is cost minimization of the entire production system and minimization of greenhouse gas emissions. Due to the NP-hard nature of the problem, the exact epsilon constraint method and MOPSO, NSGA II, and MOGWO have been used to solve the model. Also, to compare the solution methods, indices such as NPF, MSI, SM, MID, and CPU-Time have been used. The selection of the most efficient solution method has also been made with TOPSIS. The results of the calculations showed that the NSGA II is effective in obtaining the indicators of the number of effective solution and the distance index, and the MOPSO is also in obtaining the indicators of the most spread, the average computing time, and the distance from the ideal point, and the MOGWO is also in obtaining the averages of the first objective function and The second one has worked better than other algorithms. Also, the results of the implementation of the TOPSIS method for ranking the algorithms for solving the problem of a sustainable integrated production system included obtaining a desirability weight of 0.5882 for the MOPSO, obtaining a desirability weight of 0.1397 for the MOGWO, and obtaining a desirability weight of 0.7491 for the NSGA II. This article helps the integrated production system in the production units to use the discount in the production of outsourced parts. Also, the use of the new control method of uncertainty parameters helps managers in planning production correctly. Finally, the implementation of the model requires the development of solution methods, which is considered in this paper.

Keywords- Sustainable Integrated Production System; Robust-Fuzzy-Probabilistic Optimization Method; MOGWO

INTRODUCTION

Sustainability affects multiple links in the supply chain and is becoming increasingly important by all relevant stakeholders. Sustainability in supply chain management (SSCM) is becoming a necessity for businesses. With a significant increase in recent research, it is evident that the topic of sustainability in supply chain management is a topic of interest to academics and industrialists (Sharda & Banerjee, 2013). Specifically, the different goals that are proposed in the sustainability of the supply chain network are the simultaneous consideration of economic aspects such as system costs, environmental aspects such as carbon dioxide emissions, and social aspects such as human aspects (Chan et al., 2017). One of the most important members of the supply chain network are production centers, which are considered as the beating heart of the supply chain network. This member is responsible for the production of deliverable products along the supply chain network. The basic principle in production centers is to design an integrated production system to respond to customer demand (Ojstersek et al., 2020).

In manufacturing systems, mass customization is a method that provides the flexibility of process design systems such as job shop manufacturing systems with economic benefits in product design systems that include assembly lines or assembly production systems (Chu & Tsai, 1990). In the design of sustainable production systems, remanufacturing systems or combined remanufacturing-manufacturing systems can also be used due to the constructive social, economic and environmental effects. Sustainability in production systems means reducing production costs, using maximum returns and reproducing products, and increasing social responsibilities for increasing quality. The importance of sustainability in integrated production systems has led to the creation of various models and different solution methods in operations research problems. So far, countless researchers have turned to modeling such systems. Shirazi et al presented a mixed integer nonlinear programming model for mobile phone manufacturing system problem. This paper provides extensive coverage of important manufacturing features used in CMS design and increases the flexibility of the existing model in managing part demand fluctuations more economically by adding machine and PP stock decisions. The goals of the paper are to minimize the costs and balance the work load. AMOSA has been used to solve the problem (Shirazi et al., 2014). The most important topic of integrated production systems is presented to design the system model of the production system in stable conditions in this paper. The existence of different models that are not controlled in uncertainty with appropriate methods, cannot accurately show its results in the real world. Hence, this article is as follows:

- Considering the sustainable in the integrated production system (economy and environmental aspects)
- Using the machine to purchase returnable products
- Considering a discount in the production of outsourced parts
- Considering uncertainty in the model and using the new optimistic-pessimistic robust-fuzzy-probabilistic control method
- Solving the model with different meta-heuristic algorithms

As stated, the objective functions of this model is to minimize the costs of the total integrated production system and minimize the amount of greenhouse emissions. Important decisions that lead to the optimization of the objectives of the problem include determining the machines usage rate in each cell, determining the optimal level of discount, the optimal allocation of flow between the levels of the production system, the number of machines used in each cell and the number of outsourcing parts for production.

LITERATURE REVIEW

Bayram & Şahin designed a multi-period dynamic production system and designed a new mathematical model. The objective function of the mathematical model was the management of intracellular and extracellular materials, the cost of purchasing machines, reconfiguration of the plan, etc. In order to solve the problem, they used the SA and genetics and stated that the methods proposed by them are better than other solutions in terms of the quality of the answer and the solution time (Bayram & Şahin, 2016). Alhourani discussed the design of the cellular production system considering the reliability of the machines as well as the routing of the production process. He stated that considering these factors, in addition to the sequence of operations and production volume, makes the problem more complicated but more realistic. As a result, mathematical methods were used to solve the designed model (Alhourani, 2016). Arampantzi & Minis proposed a new multi-objective mixed integer linear programming (MMILP) model to study the role of sustainability in supply chain network design (SSCND), as well as significant decisions in designing or redesigning high-performance sustainable supply chains. Adopted the cost objective includes investment, operating, and pollutant costs. The environmental objective takes into account the amounts of emissions and waste generation in each link of the supply chain. Social purpose considers employment opportunities, and prioritizes the development of social community and improvement of working conditions (Arampantzi & Minis, 2017).

Ćwikła & Foit presented the assumptions, concepts, relationships and hardware and software equipment of the laboratory of integrated production systems, which provided the possibility of research and training for the integration of production and trade (Ćwikła & Foit, 2017). Nujoom et al. to evaluate a sustainable production system design considering the measurement of energy consumption and CO2 emissions using different energy sources (oil as a direct energy source for thermal energy production and oil or solar as an indirect energy source for production Electricity) addressed these problems. For this purpose, they developed a multi-objective mathematical model including economic and ecological constraints with the aim of minimizing total cost, energy consumption and CO2 emissions for a production system design.

For the real-world scenario, the uncertainty in a number of input parameters was controlled through the development of a fuzzy multi-objective model (Nujoom et al., 2018). Golpîra et al. presented a non-deterministic planning model of the integrated production system with the aim of cost minimization. They used the robust method to control the uncertain parameter of demand and supply (Golpîra et al., 2018). Rabbani et al. presented a new multi-objective mathematical model for dynamic coupled manufacturing system (DCMS) considering machine reliability and alternative process routes. In this dynamic model, the problem of integrated cellular production (cell/part/machine) as well as the assignment of operators to cells is modeled. The goals of the paper are to minimize the costs associated with DCMS, optimize the use of labor and minimize the amount of variance with work between different cells (Rabbani et al., 2019). Khezri et al. proposed an environmental multi-objective problem for a reconfigurable manufacturing system. The main goal of the problem was the simultaneous optimization of the total production time, hazardous environmental waste and the total costs of the problem. To solve the problem, they used multi-objective programming methods with GAMS software (Khezri et al., 2019).

Sadeghi et al considered the stages of design, control and production of blood sugar products in a three-level supply chain. The first step in their paper is to design a manufacturing system based on a layered cell manufacturing system (CMS), for which a mixed integer linear programming approach is proposed to minimize the number of cells required. They simulated their problem using the OptQuest feature. The results of the statistical analysis showed that the reorder point values obtained by OptQuest changed significantly compared to the ROP values estimated at the design stage (Sadeghi et al., 2020). Tirkolaee et al. discussed the prioritization of suppliers in a sustainable supply chain integrated production system using the Fuzzy Network Analysis Process (FANP) and Fuzzy Decision Evaluation (DEMATEL) methods. Prioritization of suppliers was done using TOPSIS method. After selecting the suppliers, a three-objective model of the supply chain with the objectives of quantifying the cost of the entire chain, maximizing the weighted value of the products by considering the suppliers' priorities, and maximizing the reliability of the supply chain was designed and solved using the WGP method (Tirkolaee et al., 2020). Lufika & Meutia presented an integrated green and lean production system. This study aims to analyze waste and measure energy consumption in the production process of peeled bread based on the concept of lean and green production. VSM and EVSM exist as a tool to describe the material and energy consumption flow of the production process. Research results show energy savings of up to 0.13 kWh (Lufika & Meutia. 2021).

Liu et al. proposed a new predictive maintenance method (PDM) based on deep adversarial learning enhancement (LSTM-GAN). The decision-making model provided by them considers concepts such as maintenance and maintenance personnel. Finally, they presented a case study on predictive maintenance using LSTM-GAN in intelligent manufacturing system and stated that the error prediction accuracy of LTSM-GAN is up to 99.68% (Liu et al., 2021). Goli et al. investigated the role of AGVs and human factors as indispensable components of automation systems in the cell formation and scheduling of parts under fuzzy processing time. The proposed objective function includes minimizing the makespan and intercellular movements of parts. Due to the NP-hardness of the problem, a hybrid genetic algorithm (GA/heuristic) and a whale optimization algorithm (WOA) are developed (Goli et al., 2021).

Jauhari et al. considered a two-echelon inventory model for a closed-loop supply chain system containing a manufacturer and a retailer under a stochastic environment with carbon emission reductions. The results show that by controlling the collection rate and the production allocation, the system can minimize the cost and the emissions (Jauhari et al., 2021). Sarkar & Bhuniya developed a mathematical model of this flexible manufacturing–remanufacturing system to improve the service and to maintain sustainability always. The global optimization is established theoretically and a proposition is developed (Sarkar & Bhuniya, 2022).

Utama et al. reviewed the Integrated Procurement Production (IPP) inventory model problem using a systematic review of 102 published papers from 1992 to 2021. The reviewed papers were based on complexity, type of model, data, time dynamics, optimization, solution, and paper (Utama et al., 2022). Ghahremani-Nahr & Ghaderi designed a lean supply chain under uncertainty and used Fuzzy-Robust optimization model to control the uncertainty parameters. The model's objective functions are to minimize the total cost of designing LSC networks (economic aspect), to minimize waste in production units (environmental aspect), and to maximize the overall sustainability performance indicator (SPI) (social aspect). To achieve these objectives and to identify the Pareto front, we investigated both exact and meta-heuristic methods (Ghahremani-Nahr & Ghaderi, 2022).

Yu & Khan developed a three-level supply chain composed of plants, distribution centers, and retailers, and studied the location of distribution centers in the supply chain network and the carbon emissions during processing and transportation. In a random and fuzzy environment, the research objective is to minimize the supply chain's cost and carbon emission (Yu & Khan, 2022). The importance of two economic and environmental aspects in production system problems has led to the modeling of a dual-objective problem of a sustainable integrated production system in which the return of products and the reproduction of products to reduce environmental effects are also considered in this paper. Be paid Also, the sustainable of the system has been discussed under the title of maximum use of returned products to reproduce new orders and apply discounts in the production of outsourced parts. In the following, in Table (1), a comparison of the published papers in the field of integrated production system and research gap has been discussed.

After examining the research gap of the problem, in this paper, a bi-objective model for a sustainable integrated production system with the bi-objective of minimizing system costs and minimizing the amount of greenhouse gas emissions and considering the sustainability of the system under the title of maximum use of returnable products It is provided to reproduce new orders and apply discounts in the production of outsourced parts. Therefore, according to the literature on the subject, so far, the discussion of the reduction in outsourcing production costs in a sustainable integrated production system under uncertainty has not been addressed. Optimistic-pessimistic robust-fuzzy-probabilistic control method as a new method in controlling model parameters has led to its complexity. Also, the MOGWO is used to solve the problem and compare it with the NSGA II and MOPSO in this paper.

As a result, the most important innovations of the article are as follows:

- Integration of integrated production system with sustainability concepts
- Using the Optimistic-pessimistic robust-fuzzy-probabilistic
- Applying discounts in the production of outsourced products in the production system
- Development of innovative methods

TABLE 1
A SUMMARY OF THE LITERATURE REVIEW

Author	Year	Economic aspect	environmental	Social aspect	multi-product	multi-period	uncertainty	solution method	Offer discounts
Kia et al	2014	*	-	-	*	-	-	SA	-
Shirazi et al	2014	*	-	*	-	-	-	AMOSA	-
Bayram & Şahin	2016	*	-	-	-	*	-	SA GA	-
Tavakoli et al	2018	-	-	*	*	-	-	GAMS	-
Golpîra et al	2018	*	-	-	-	-	Robust	Cplex	-
Rabbani et al	2019	-	*	*	*	-	-	NSGA II MOPSO	-
Khezri et al	2019	*	*	-	-	*	-	Cplex	-
Dehnavi-Arani et al	2019	*	-	-	*	-	-	GAMS	-
Raoofpanah et al	2019	*	-	-	*	*	-	ICA	-
Ghanei et al	2020	*	*	-	-	*	-	GA	-
Tang et al	2020	*	-	-	-	*	-	Cplex	-
Assid et al	2020	*	-	-	-	*	Fuzzy	SA	-
Mohtashami et al	2020	*	*	-	*	-	-	NSGA II	-
Goli et al.	2021	*	-	-	-	-	-	WOA	-
Jauhari et al.	2021	*	*	-	*	-	Stochastic	GAMS	-
Ghahremani-Nahr & Ghaderi	2022	*	*	*	*	*	Robust-Fuzzy	MOGWO	-
Yu & Khan	2022	*	*		*		Fuzzy	GAMS	-
Salehi-Amiri et al.	2022	*		*		*	-	GAMS	-
Rajak et al.	2022	*	*		*		-	GAMS	-
current paper	2022	*	*	-	*	-	robust-fuzzy-probabilistic	NSGA II MOPSO MOGWO	Discounts on production outsourcing

PROBLEM DEFINITION

Based on Fig. 1. The main goal of this research is optimal allocation of parts to machines for processing and also optimal allocation of machines to each cell. In this paper, some parts are produced in the production center and some parts are outsourced by paying a discounted production cost. Therefore, finding the amount of parts that can be processed inside the collection or outsourcing the process is also one of the most important goals of the research.

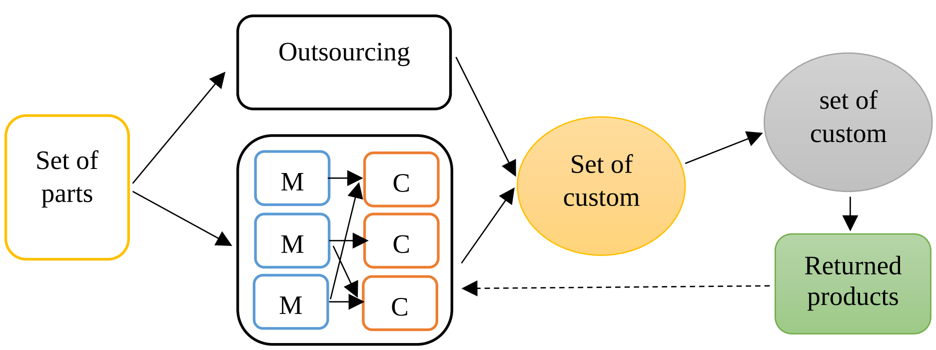

FIGURE 1
SUSTAINABLE INTEGRATED PRODUCTION SYSTEM

Correcting strategic and tactical decisions with the aim of optimizing the costs of the entire integrated production system and the amount of greenhouse gas emissions. Since in this paper the demand, operating costs, outsourced production cost, transportation, and processing time are considered probabilistically and under conditions of uncertainty, the Robust-fuzzy-probabilistic optimization method is used to control uncertainty parameters.

The assumptions of the sustainable integrated production system model are as follows:

- It is a single-period and multi-product model.
- The cost of production by foreign producers is considered by applying discounts.
- Demand, operating costs, outsourced production cost, transportation and processing time are considered uncertainty and trapezoidal fuzzy numbers and in different scenarios.
- The production capacity is certain and certain.
- Each cell has a minimum and maximum limit on the allocation of machines.

Based on the definition of the above problem, the set, parameters and decision variables of the sustainable integrated production system model are described as follows.

Sets

I	Set of all kinds of parts
M	Set of machines
C	Collection of cells
J	Set of returned products
S	A set of scenarios
B	Set of discount levels

Parameters

$\tilde{D}_i^s$	Demand for segment i in scenario s
$\tilde{E}_i$	Production cost per unit of parts i
$\tilde{W}_i$	The cost of transporting materials inside the cell for each piece i
$\tilde{T}_{im}$	Processing time of each piece i on machine m
σ_m	Machine maintenance cost m
ε_m	The cost of buying a machine m
β_m	The cost of operation on the machine m
μ_m	Machine capacity m
L_c	Lower cell size limit c
U_c	Upper cell size limit c
ξ_i	Average recycling rate of part i
γ_{im}	If piece i is processed by machine m, it takes the value 1 and otherwise 0.
$\tilde{O}_{ib}^s$	Outsourcing cost of part i in scenario s at discount level b
Lo_{ib}^s	The lower limit of the production discount interval of piece i in scenario s at the discount level b
B_{ji}	Number of parts i used in product j
$\emptyset_j$	Unit cost to obtain return product j
k_j	Setup cost for disassembly of returned product j
τ_j	The cost of dismantling the returned product j
χ_j	The cost of destroying the returned product j
$MTBF_m$	The average time between two consecutive failures of the machine m
$MTTR_m$	The average time between two consecutive machine repairs is m
Q_m	The cost of machine breakdown m
P_s	The probability of occurrence of scenario s
Co_{imc}	The amount of carbon dioxide emissions due to the processing of a piece i on machine m in cell c
C_j	The amount of carbon dioxide gas emitted during the disassembly of the product j
G_{mc}	The amount of carbon dioxide gas emission in starting machine m in cell c

Decision variables

λ_{imc}^{s}	Arrival rate of part i on machine m in cell c in scenario s
Q_{i}^{s}	The number of outsourced parts i in scenario s
Z_{imc}^{s}	If piece i is processed on machine m in cell c in scenario s, the value is 1 and otherwise it is 0.
N_{mc}	The number of machines m used in cell c
ζ_{m}	The number of machines m to be purchased.
ρ_{m}	machines usage rate m
d_{j}	The number of returned product j for disassembly
r_{j}	The number of return product j to be obtained
δ_{j}	If the returned product j is disassembled, it takes the value 1 and otherwise 0.
α_{mc}	If machines m is assigned to cell c, it gets 1 value and otherwise 0.
X_{ic}	If the piece i is processed in cell c, it takes the value 1 and otherwise 0.
M_{ibs}	If part i is assigned at the discount level b for outsourcing in scenario s, it will be assigned a value of 1, and otherwise it will be 0.

The integrated production system dual-objective problem is modeled as a mixed integer linear mathematical model under uncertainty conditions as below.

$$\begin{aligned}minZ_1 = &\sum_s\sum_i\sum_m\sum_c P_s.\tilde{T}_{im}.\lambda_{imc}^s.\beta_m.\left(1+\frac{MTTR_m}{MTBF_m}\right)+\\ &\sum_s\sum_i\sum_m\sum_c P_s.\tilde{T}_{im}.\frac{\lambda_{imc}^s}{MTBF_m}.Q_m+\sum_i\sum_s\sum_b P_s.\tilde{O}_{ib}^s.\psi_{ib}^s+\\ &\sum_s\sum_i\sum_m\sum_c P_s.\tilde{E}_i.\lambda_{imc}^s\sum_i\sum_m\sum_c \widetilde{W}_i.\gamma_{im}.X_{ic}-\sum_i\sum_m\sum_c \widetilde{W}_i.\gamma_{im}.F_{icm}+\\ &\sum_m\sum_c \sigma_m.N_{mc}+\sum_m \varepsilon_m.\zeta_m+\sum_j \emptyset_j.r_j+k_j.\delta_j+\tau_j.d_j+\sum_j\sum_i(1-\xi_i).\chi_j.B_{ji}.d_j\end{aligned} \tag{1}$$

$$minZ_2 = \sum_s\sum_i\sum_m\sum_c P_s.Co_{imc}.\lambda_{imc}^s+\sum_j C_j.d_j+\sum_m\sum_c G_{mc}.N_{mc} \tag{2}$$

$s.t.$:

$$\sum_b Q_{ib}^s+\sum_m\sum_c \lambda_{imc}^s=\widetilde{D}_i^s, \quad \forall i,s \tag{3}$$

$$Z_{imc}^s \le \gamma_{im}, \quad \forall i,m,c,s \tag{4}$$

$$\lambda_{imc}^s \le BigM.Z_{imc}^s, \quad \forall i,m,c,s \tag{5}$$

$$\sum_i T_{im}.\lambda_{imc}^s \le \mu_m.N_{mc}, \quad \forall m,c,s \tag{6}$$

$$L_c \le \sum_m N_{mc} \le U_c, \quad \forall c \tag{7}$$

$$\sum_c N_{mc} \le \zeta_m, \quad \forall m \tag{8}$$

$$\sum_i\sum_c\sum_s \frac{\lambda_{imc}^s}{\mu_m}=\rho_m, \quad \forall m \tag{9}$$

$$\rho_m \le 1, \quad \forall m \tag{10}$$

$$\sum_m\sum_c\sum_s \lambda_{imc}^s \le \xi_i\sum_j B_{ji}.d_j, \quad \forall i \tag{11}$$

$$r_j \ge d_j, \quad \forall j \tag{12}$$

$$d_j \le BigM.\delta_j, \quad \forall j \tag{13}$$

$$N_{mc} \le BigM.\alpha_{mc}, \quad \forall m,c \tag{14}$$

$$\alpha_{mc} \le N_{mc}, \quad \forall m,c \tag{15}$$

$$\sum_{m}\sum_{s} Z_{imc}^{s} \leq BigM.X_{ic}, \quad \forall i,c \tag{16}$$
$$\sum_{m}\sum_{s} Z_{imc}^{s} \geq X_{ic}, \quad \forall i,c \tag{17}$$
$$F_{icm} \leq X_{ic}, \quad \forall i,m,c \tag{18}$$
$$F_{icm} \leq \alpha_{mc}, \quad \forall i,m,c \tag{19}$$
$$X_{ic} + \alpha_{mc} - F_{icm} \leq 1, \quad \forall i,m,c \tag{20}$$
$$\sum_{s} Z_{imc}^{s} = F_{imc}, \quad \forall i,m,c \tag{21}$$
$$M_{ibs}Lo_{ib}^{s} \leq \ Q_{ib}^{s}, \quad \forall i,b,s \tag{22}$$
$$\sum_{b} M_{ibs} = 1, \quad \forall i,s \tag{23}$$
$$\psi_{ib}^{s} \leq Q_{ib}^{s}M_{ibs}, \quad \forall i,b,s \tag{24}$$
$$\psi_{ib}^{s} \leq BigM.M_{ibs}, \quad \forall i,b,s \tag{25}$$
$$\psi_{ib}^{s} \geq Q_{ib}^{s} - BigM.(1 - M_{ibs}), \quad \forall i,b,s \tag{26}$$
$$\lambda_{imc}^{s}, Q_{ib}^{s}, N_{mc}, \zeta_{m}, d_{j}, r_{j} \geq 0 \ \ and\ integer \tag{27}$$
$$Z_{imc}^{s}, \rho_{m}, \delta_{j}, \alpha_{mc}, X_{ic}, M_{ibs} \in \{0,1\} \tag{28}$$

Equation (1) shows the first objective function of the problem and includes minimizing the costs of the entire integrated production system, including production costs, purchase of machines, processing costs, transportation and outsourcing. Equation (2) shows the second objective function of the problem and includes minimizing the amount of greenhouse gas emissions caused by the production and reproduction of products and parts. Relationship (3) shows that the demand of each piece in each scenario will be met by production in the complex or outsourcing. Equation (4) guarantees that the processing of parts by machines is based on the processing capability of each machine. The relation (5) shows that the parts will be processed by the machine if the machine is assigned to the part processing. Equation (6) guarantees that the processing of parts should not exceed the capacity of the machines. Equation (7) guarantees that the total number of machines allocated to each cell should not exceed a lower and upper bound. Equation (8) guarantees that the total number of machines in the cell must be less than the total number of purchased machines. Equation (9) calculates and shows the productivity of each machine.

Equation (10) guarantees that the utilization rate of machines must be less than 1. Equation (11) shows the total number of returned products. Equation (12) calculates the number of products that must be disassembled. Equation (13) guarantees that a product must be disassembled that is already selected. Equation (14) and (15) shows how to allocate machines to each cell. Equation (16) and (17) shows how to assign each part to the corresponding machine and cell. Relations (18) to (21) are the limitations related to the linearization of the model. Relations (22) and (23) show the restrictions related to the application of discounts. Relations (24) to (26) show the linearization of discount limits. Relationships (27) and (28) show the type and gender of decision making variables.

Due to the dynamic and fluctuating nature of some important parameters (including demand, operating costs, production outsourcing cost and processing time) that are beyond planning, as well as the unavailability and even unobtainability of the required historical data at the design stage, these parameters are mainly It is estimated based on the opinions and subjective experiences of experts; Therefore, the above fuzzy parameters are formulated as uncertainty data in the form of trapezoidal fuzzy numbers. It is worth noting that for long-term decisions, it is difficult and sometimes impossible to evaluate demand, operational costs and processing time. Even if one can estimate a probability distribution function for these parameters, it is possible that these parameters do not behave the same as the past data. Therefore, these parameters that change in a long-term planning horizon are considered as fuzzy data. According to the uncertainty parameters, the model controlled by the robust-fuzzy-probabilistic optimization method is as follows:

$$minZ_1 = E[Z] + \xi(Zmax - Zmin) + \omega \sum_s P_s\{E[Z] - E[Z_s] + 2\theta_s\}$$
$$+\eta \sum_i \sum_s P_s \left[D_i^{s-4} - \frac{(\alpha_s - \lambda) D_i^{s(3)} + (1-\alpha_s) D_i^{s(3)}}{1-\lambda} \right] \tag{29}$$

$$minZ_2 = \sum_s \sum_i \sum_m \sum_c P_s . Co_{imc} . \lambda_{imc}^s + \sum_j C_j . d_j + \sum_m \sum_c G_{mc} . N_{mc} \tag{30}$$

$s.t.:$

$$\sum_b Q_{ib}^s + \sum_m \sum_c \lambda_{imc}^s =$$
$$\left[(1-\nu)\left[(1-\alpha_s) D_i^{s(3)} + \alpha_s D_i^{s(4)}\right] + (\nu)\left[(1-\alpha_s) D_i^{s(1)} + \alpha_s D_i^{s(2)}\right]\right], \qquad \forall i, s \tag{31}$$

$$Zmin = \sum_s \sum_i \sum_m \sum_c P_s . T_{im}^1 . \lambda_{imc}^s . \beta_m . \left(1 + \frac{MTTR_m}{MTBF_m}\right) +$$
$$\sum_s \sum_i \sum_m \sum_c P_s . T_{im}^1 . \frac{\lambda_{imc}^s}{MTBF_m} . Q_m + \sum_i \sum_s \sum_b P_s . O_{ibs}^1 . \psi_{ib}^s +$$
$$\sum_s \sum_i \sum_m \sum_c P_s . E_i^1 . \lambda_{imc}^s + \sum_i \sum_m \sum_c W_i^1 . \gamma_{im} . (X_{ic} - F_{icm}) + \tag{32}$$
$$\sum_m \sum_c \sigma_m . N_{mc} + \sum_m \varepsilon_m . \zeta_m + \sum_j \emptyset_j . r_j + k_j . \delta_j + \tau_j . d_j + \sum_j \sum_i (1-\xi_i) . \chi_j . B_{ji} . d_j$$

$$Zmax = \sum_s \sum_i \sum_m \sum_c P_s . T_{im}^4 . \lambda_{imc}^s . \beta_m . \left(1 + \frac{MTTR_m}{MTBF_m}\right) +$$
$$\sum_s \sum_i \sum_m \sum_c P_s . T_{im}^4 . \frac{\lambda_{imc}^s}{MTBF_m} . Q_m + \sum_i \sum_s \sum_b P_s . O_{ibs}^4 . \psi_{ib}^s +$$
$$\sum_s \sum_i \sum_m \sum_c P_s . E_i^4 . \lambda_{imc}^s + \sum_i \sum_m \sum_c W_i^4 . \gamma_{im} . (X_{ic} - F_{icm}) + \tag{33}$$
$$\sum_m \sum_c \sigma_m . N_{mc} + \sum_m \varepsilon_m . \zeta_m + \sum_j \emptyset_j . r_j + k_j . \delta_j + \tau_j . d_j + \sum_j \sum_i (1-\xi_i) . \chi_j . B_{ji} . d_j$$

$$E[Z_s] = \sum_c \sum_i \sum_m \left[\left(\frac{1-\lambda}{2}\right)(T_{im}^1 + T_{im}^2) + \left(\frac{\lambda}{2}\right)(T_{im}^3 + T_{im}^4)\right] . \lambda_{imc}^s . \beta_m . \left(1 + \frac{MTTR_m}{MTBF_m}\right)$$
$$+ \sum_c \sum_i \sum_m \left[\left(\frac{1-\lambda}{2}\right)(T_{im}^1 + T_{im}^2) + \left(\frac{\lambda}{2}\right)(T_{im}^3 + T_{im}^4)\right] . \frac{\lambda_{imc}^s}{MTBF_m} . Q_m +$$
$$\sum_i \sum_b \left[\left(\frac{1-\lambda}{2}\right)(O_{ibs}^1 + O_{ibs}^2) + \left(\frac{\lambda}{2}\right)(O_{ibs}^3 + O_{ibs}^4)\right] . \psi_{ib}^s +$$
$$\sum_c \sum_i \sum_m \left[\left(\frac{1-\lambda}{2}\right)(E_i^1 + E_i^2) + \left(\frac{\lambda}{2}\right)(E_i^3 + E_i^4)\right] . \lambda_{imc}^s + \tag{34}$$
$$\sum_i \sum_m \sum_c \left[\left(\frac{1-\lambda}{2}\right)(W_i^1 + W_i^2) + \left(\frac{\lambda}{2}\right)(W_i^3 + W_i^4)\right] . \gamma_{im} . (X_{ic} - F_{icm}) +$$
$$\sum_m \sum_c \sigma_m . N_{mc} + \sum_m \varepsilon_m . \zeta_m + \sum_j \emptyset_j . r_j + k_j . \delta_j + \tau_j . d_j + \sum_j \sum_i (1-\xi_i) . \chi_j . B_{ji} . d_j , \qquad \forall s$$

$$E[Z] = \sum_s \sum_i \sum_m \sum_c P_s . \left[\frac{T_{im}^1 + T_{im}^2 + T_{im}^3 + T_{im}^4}{4}\right] . \lambda_{imc}^s . \beta_m . \left(1 + \frac{MTTR_m}{MTBF_m}\right) +$$
$$\sum_s \sum_i \sum_m \sum_c P_s . \left[\frac{T_{im}^1 + T_{im}^2 + T_{im}^3 + T_{im}^4}{4}\right] . \frac{\lambda_{imc}^s}{MTBF_m} . Q_m + \tag{35}$$
$$\sum_i \sum_s \sum_b P_s . \left[\frac{O_{ibs}^1 + O_{ibs}^2 + O_{ibs}^3 + O_{ibs}^4}{4}\right] . \psi_{ib}^s +$$

$$\sum_s \sum_i \sum_m \sum_c P_s.\left[\frac{E_i^1 + E_i^2 + E_i^3 + E_i^4}{4}\right].\lambda_{imc}^s + \sum_i \sum_m \sum_c \left[\frac{W_i^1 + W_i^2 + W_i^3 + W_i^4}{4}\right].\gamma_{im}.(X_{ic} - F_{icm}) + \sum_m \sum_c \sigma_m.N_{mc} + \sum_m \varepsilon_m.\zeta_m + \sum_j \emptyset_j.r_j + k_j.\delta_j + \tau_j.d_j + \sum_j \sum_i (1-\xi_i).\chi_j.B_{ji}.d_j$$

Constraint (4) to (28) (36)

In the above relationships, α_s shows the minimum degree of certainty of establishing an uncertain limit with an optimistic-pessimistic combined decision-making approach. ν is a parameter of zero and one, and if ν takes a value of 1, the combined fuzzy model turns into an optimistic fuzzy model, and if ν takes a value of 0, the combined fuzzy model turns into a pessimistic fuzzy model. Also, if ν takes a value of 0.5, the combined fuzzy model becomes a moderate fuzzy model. η also represents the penalty cost of not estimating the demand for fuzzy levels of numbers. Due to the NP-Hard and bi-objectiveness of the integrated production system problem under uncertainty conditions, NSGA II, MOPSO and MOGWO have been used to solve larger sample size problems. Therefore, in the following, the design of the initial solution of the problem as well as the comparison indicators of multi-objective algorithms are discussed.

SOLUTION METHODS

- ***Initial Solution design***

In this section, the initial solution design of the problem for MOPSO, NSGA II and MOGWO is discussed. According to Fig. 2, suppose 3 types of parts, 4 types of machines and 2 cells are considered in each scenario for the production of products. Table. 2, shows the initial solution of the problem.

TABLE 2
THE INITIAL SOLUTION OF THE SUSTAINABLE INTEGRATED PRODUCTION SYSTEM PROBLEM

Part	**Cell**	**Machine**			
		1	2	3	4
1	1	0	5	0	10
	2	15	0	20	0
2	1	0	0	6	5
	2	10	7	0	0
3	1	6	0	0	6
	2	0	18	12	0

In the above figure, a matrix of random numbers is created, which is defined as the rate of arrival of parts to each machine and in each cell. If the intersection of the row and column of the matrix is 0, it means that the machine is not assigned to that cell to process parts in each scenario. After assembling the parts and based on the customer's demand, the difference between the demand and the produced parts is ordered to the foreign manufacturer as outsourced parts.

- ***Comparison indices of multi-objective meta-heuristic algorithms***

The following indicators are defined in order to compare meta-heuristic algorithms in the production of efficient solutions by MOPSO, NSGA II and MOGWO. Calculation time (CPU-Time): An algorithm that has less calculation time will be more desirable. The number of solutions in Pareto (NPF): shows the number of non-defeated solutions in the Pareto set obtained for each problem, and the higher the number of these points, the more effective the algorithm.

Maximum expansion: This criterion shows how much of the solutions of a Pareto set in the distributed solution space is calculated from equation (37). The larger value of this criterion indicates the appropriate diversity of solutions of the Pareto set.

$$MSI = \sqrt{\sum_{m=1}^{M} \left(max_{i=1:|Q|} f_m^i - max_{j=1:|Q|} f_m^j\right)^2} \tag{37}$$

Spacing: indicates the level of placement of the solution uniformly together, which is calculated from equation (38).

$$SM = \sqrt{\frac{1}{|Q|} \sum_{i=1}^{|Q|} (d_i - \bar{d})^2} \tag{38}$$

In the above relation, |Q| It represents the size of the Pareto archive and the value of d¯can be calculated from equation (39). An algorithm with a lower value of this criterion will be more desirable.

$$\bar{d} = \sum_{i=1}^{|Q|} \frac{min_{k \in Q \cap k \neq i} \sum_{m=1}^{M} \left|f_m^i - f_m^k\right|}{|Q|} \tag{39}$$

Distance from the ideal point: This criterion is used to measure the degree of closeness to the real Pareto optimal level, which is calculated from equation (40). The algorithm that has the lowest value of this index has a higher efficiency.

$$MID = \frac{\sum_{i=1}^{n} \sqrt{(f_{1i} - f_1^*)^2 + (f_{2i} - f_2^*)^2 + \cdots + (f_{mi} - f_m^*)^2}}{n} \tag{40}$$

In this relation, n is the number of solutions in the Pareto optimal set.

- ***Parameter tuning of meta-heuristic algorithms***

In this section, the parameter tuning of the proposed meta-heuristic algorithms in solving the bi-objective model of the integrated production system using the Taguchi method has been discussed. In this method, for each parameter of meta-heuristic algorithm, three proposed levels are considered, and based on Taguchi table, relevant tests are performed using relations (41) and (42). The results of the tests after the analysis show the best parameter value of the mentioned algorithm. In relation (41), S_i is the index value obtained from each Taguchi test and S_i^* is the best index value among all Taguchi tests.

$$S_i = \left|\frac{NPF + MSI + SM + MID + CPU\_time}{5}\right| \tag{41}$$

$$RPD = \frac{S_i - S_i^*}{S_i^*} \tag{42}$$

Table (3) shows the recommended and optimal parameter levels of NSGA II, MOPSO and MOGWO.

TABLE 3
SUGGESTED PARAMETER LEVELS FOR PARAMETER TUNING OF META-HEURISTIC ALGORITHMS USING TAGUCHI METHOD

Algorithm	parameter	symbol	Level 1	Level 2	Level 3	Optimal level
MOGWO	Number of population	NWolf	100	200	500	500
	Maximum number of iterations	Max it	100	200	300	200
	crossover rate	A	1	2	4	4
	Mutation rate	C	1	2	4	1
NSGA II	Maximum number of iterations	Max it	100	200	500	500
	Number of population	Npop	100	200	300	200
	crossover rate	Pc	0.1	0.3	0.5	0.5
	Mutation rate	Pm	0.1	0.3	0.5	0.1
MOPSO	Maximum number of iterations	Max it	100	200	500	500
	Number of ppapers	Nparticle	100	200	300	200
	Individual recruitment coefficient	C1	1	1.5	2	2
	Coefficient of collective learning	C2	1	1.5	2	2
	Gravity coefficient	W	0.6	0.6	0.7	0.5

EXPERIENCE AND ANALYSIS OF EXPERIMENTS

After tuning the parameters and presenting the comparison indices of the algorithms, in this section, the analysis of sample problems in different sizes has been done. Therefore, 15 sample problems are designed in three sizes, small, medium and large according to Table (5) and based on the random data provided according to the uniform distribution function according to Table (4). Due to the bi-objective of the mathematical model, NSGA II, MOPSO, MOGWO and epsilon constraint methods have been used to solve the sample problems. It should also be mentioned that due to the use of the combined robust-fuzzy-probabilistic optimization method, the values related to the control method of the problem parameter are considered as $\lambda = 0.5, \sum_s \alpha_s = 1$.

TABLE 4

INTERVAL LIMITS OF PROBLEM PARAMETERS BASED ON UNIFORM DISTRIBUTION FUNCTION

parameter	*Interval boundaries*	*parameter*	*Interval boundaries*	*parameter*	*Interval boundaries*
σ_m	$\sim U[5,10]$	B_{ji}	$\sim U[1,2]$	μ_m	$\sim U[30,40]$
ε_m	$\sim U[30,60]$	$\emptyset_j, k_j, \tau_j$	$\sim U[100,500]$	L_c	2
β_m	$\sim U[1,2]$	χ_j	$\sim U[7,9]$	U_c	10
G_{mc}	$\sim U[100,190]$	$MTBF_m$	$\sim U[20,30]$	ξ_i	0.3
$MTTR_m$	$\sim U[10,20]$	Q_m	$\sim U[120,230]$	γ_{im}	$\sim U[0,1]$
		C_j	$\sim U[120,180]$	Co_{imc}	$\sim U[150,200]$
$\tilde{O}_{ib}^s$	$\sim U[(2000,2500),(2500,2800),(2800,3000),(3000,3200)]$				
$\tilde{T}_{im}$	$\sim U[(2,4),(4,6),(6,8),(8,10)]$				
$\tilde{D}_i^s$	$\sim U[(50,60),(60,70),(70,80),(80,90)]$				
$\tilde{E}_i, \tilde{W}_i$	$\sim U[(1,2),(2,3),(3,4),(4,5)]$				

TABLE 5

THE SIZE OF SAMPLE PROBLEMS IN SMALL, MEDIUM AND LARGE SIZES

Sample problem	*size*	*Part*	*cell*	*Machine*	*product*	*scenario*	*Discount level*
1		*2*	*5*	*6*	*2*	*2*	*3*
2		*3*	*5*	*7*	*2*	*2*	*3*
3	*small*	*4*	*6*	*7*	*2*	*2*	*3*
4		*5*	*6*	*8*	*3*	*2*	*3*
5		*6*	*7*	*8*	*3*	*3*	*3*
6		*8*	*8*	*9*	*4*	*3*	*3*
7		*10*	*8*	*9*	*4*	*4*	*4*
8	*medium*	*12*	*10*	*10*	*6*	*4*	*4*
9		*14*	*10*	*12*	*6*	*5*	*4*
10		*16*	*12*	*15*	*8*	*5*	*5*
11		*20*	*15*	*18*	*10*	*6*	*5*
12		*25*	*18*	*21*	*12*	*6*	*5*
13	*large*	*30*	*21*	*24*	*14*	*8*	*6*
14		*35*	*24*	*28*	*16*	*8*	*6*
15		*40*	*28*	*30*	*20*	*10*	*6*

After designing the sample problems, in order to compare the results, the averages of the first objective function and the second objective function of the problem as well as the average computing time obtained from 3 repetitions of the algorithm are shown in Table (5). According to the results obtained from table (6), it can be seen that the epsilon constraint method is only able to solve small sample size problems up to the 5th sample problem. Therefore, to solve other sample problems in medium and large sizes, NSGA II, MOPSO and MOGWO have been used. Also, by comparing the averages of the first and second objective functions in small sample problems between the exact solution method and meta-heuristic methods He stated that there is no significant difference between the averages of the three mentioned indicators and therefore these algorithms can be used to solve problems in other sizes. Fig. 4, shows the averages of the first objective function, the second objective function, and the computational time obtained from solving sample problems in small, medium, and large sizes by epsilon constraint methods, NSGA II, MOPSO,

TABLE 6
AVERAGE OBJECTIVE FUNCTIONS AND COMPUTATIONAL TIME OBTAINED FROM SOLVING SAMPLE PROBLEMS

Sample problem	*NSGA II*			*MOPSO*			*MOGWO*			*Epsilon Constraint*		
	MOBF1	*MOBF2*	*Cpu time*	*MOBF1*	*MOBF2*	*Cpu time*	*MOBF1*	*MOBF2*	*Cpu time*	*MOBF1*	*MOBF2*	*Cpu time*
1	*6948.82*	*2080.08*	*18.64*	*6840.49*	*2085.40*	*26.34*	*6789.72*	*2074.17*	*27.64*	*6809.24*	*2090.67*	*146.24*
2	*7344.16*	*2234.89*	*26.18*	*7449.75*	*2262.20*	*34.28*	*7330.59*	*2228.85*	*40.16*	*7393.56*	*2247.03*	*233.16*
3	*8872.83*	*2607.91*	*37.20*	*8900.06*	*2574.83*	*45.68*	*8988.29*	*2564.46*	*53.63*	*8915.31*	*2580.51*	*479.15*
4	*9990.10*	*3549.59*	*49.63*	*9886.18*	*3604.47*	*66.47*	*9843.51*	*3503.22*	*77.81*	*9901.49*	*3656.44*	*719.20*
5	*11254.80*	*4246.54*	*72.24*	*11042.61*	*4244.82*	*91.10*	*11205.70*	*4302.83*	*106.86*	*11136.43*	*4259.75*	*1057.66*
6	*12759.95*	*4820.19*	*103.60*	*12590.46*	*4912.48*	*124.33*	*12914.79*	*4735.45*	*146.09*	-	-	-
7	*14935.33*	*5532.13*	*155.44*	*15062.40*	*5532.23*	*178.67*	*14875.15*	*5538.08*	*210.26*	-	-	-
8	*15433.58*	*7558.71*	*237.13*	*15415.73*	*7425.56*	*256.64*	*15382.22*	*7606.14*	*312.92*	-	-	-
9	*17238.10*	*7960.45*	*327.99*	*17362.57*	*7814.75*	*368.82*	*17326.34*	*7894.21*	*434.40*	-	-	-
10	*19326.91*	*8267.58*	*420.54*	*18995.60*	*8274.74*	*476.15*	*19274.07*	*8107.35*	*560.66*	-	-	-
11	*20092.10*	*9382.97*	*547.17*	*19768.00*	*9502.38*	*610.07*	*20481.13*	*9258.05*	*718.77*	-	-	-
12	*25855.32*	*11382.97*	*691.34*	*26183.73*	*11484.25*	*776.53*	*25448.06*	*11324.88*	*914.63*	-	-	-
13	*26319.01*	*14002.01*	*826.64*	*25950.40*	*14091.40*	*964.49*	*26001.20*	*13996.23*	*1134.42*	-	-	-
14	*29107.44*	*15316.96*	*1010.15*	*29129.09*	*15606.74*	*1144.20*	*28920.56*	*15593.66*	*1347.27*	-	-	-
15	*29241.95*	*20348.24*	*1247.64*	*29416.22*	*20592.69*	*1386.47*	*29733.60*	*19984.15*	*1633.71*	-	-	-
Average	*16981.36*	*7952.75*	*384.77*	*16932.89*	*8000.60*	*436.68*	*16967.66*	*7914.12*	*514.62*			

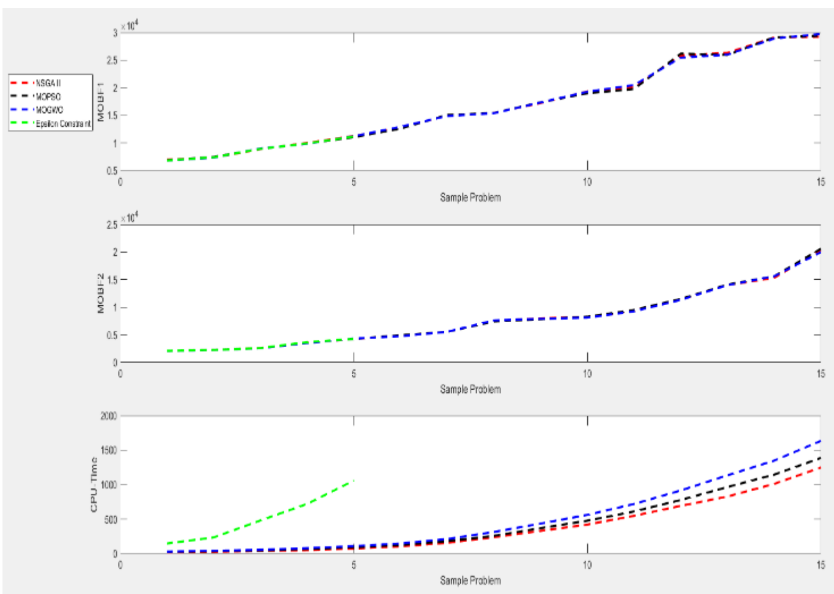

FIGURE 2
COMPARISON OF AVERAGES OF OBJECTIVE FUNCTIONS AND COMPUTATIONAL TIME BETWEEN DIFFERENT SOLUTION METHODS IN SMALL TO LARGE SIZE PROBLEMS

According to Fig. 2., it can be seen that with the increase in the size of the problem, due to the increase in the number of parts and products for production or outsourcing, the costs related to the integrated production system, as well as the amount of greenhouse gas emissions due to production, reproduction, etc., have increased. Also, according to Fig. 4, it can be seen that with the increase in the problem size, the problem solving time by the epsilon constraint method up to sample problem 5 was much higher than other meta-heuristic algorithms. This is despite the fact that the averages of the first and second objective functions between the meta-heuristic and epsilon constraint solving methods are close to each other without significant differences. Also, the exponentiality of the problem solving time in larger sizes shows that the problem of the sustainable integrated production system designed in this paper is NP-hard.

TABLE 7
COMPARISON INDICES OF META-HEURISTIC ALGORITHMS IN SMALL TO LARGE SAMPLE SIZE PROBLEMS

Sample	*NSGA II*				*MOPSO*				*MOGWO*			
problem	*NPF*	*MSI*	*SM*	*MID*	*NPF*	*MSI*	*SM*	*MID*	*NPF*	*MSI*	*SM*	*MID*
1	*47*	*22033.25*	*37528.19*	*0.51*	*54*	*31617.83*	*32249.03*	*0.68*	*73*	*35276.88*	*42055.46*	*0.80*
2	*57*	*20785.35*	*34250.97*	*0.49*	*62*	*30805.16*	*44184.28*	*0.61*	*68*	*36110.20*	*39476.36*	*0.54*
3	*74*	*38664.58*	*45863.14*	*0.53*	*63*	*34108.82*	*42770.83*	*0.48*	*46*	*22085.06*	*37154.13*	*0.48*
4	*52*	*39431.84*	*32908.87*	*0.58*	*59*	*20100.58*	*41883.66*	*0.68*	*65*	*29395.18*	*39511.57*	*0.67*
5	*73*	*27218.56*	*39722.85*	*0.69*	*62*	*35650.32*	*39722.45*	*0.42*	*70*	*24381.24*	*43420.44*	*0.79*
6	*85*	*32884.11*	*30256.91*	*0.60*	*80*	*38537.19*	*41357.05*	*0.47*	*48*	*38454.16*	*49192.90*	*0.65*
7	*45*	*21658.95*	*33732.24*	*0.55*	*66*	*20164.91*	*38530.09*	*0.42*	*52*	*26406.45*	*31781.69*	*0.43*
8	*73*	*24158.24*	*39704.61*	*0.76*	*79*	*36492.57*	*31527.79*	*0.75*	*74*	*37150.88*	*45954.85*	*0.55*
9	*78*	*20792.08*	*46764.52*	*0.79*	*62*	*35346.72*	*35711.73*	*0.74*	*96*	*25196.93*	*41815.51*	*0.47*
10	*62*	*29387.19*	*32820.14*	*0.65*	*60*	*39942.74*	*41226.70*	*0.45*	*76*	*37561.26*	*48243.94*	*0.49*
11	*75*	*23001.93*	*44644.34*	*0.45*	*72*	*34553.06*	*42666.67*	*0.56*	*78*	*23765.35*	*32032.59*	*0.42*
12	*49*	*39826.15*	*43821.34*	*0.65*	*71*	*38390.84*	*48615.52*	*0.45*	*45*	*35183.88*	*35865.89*	*0.76*
13	*72*	*28541.25*	*30689.85*	*0.55*	*60*	*32839.99*	*49555.38*	*0.63*	*58*	*20633.79*	*30321.76*	*0.72*
14	*78*	*39107.40*	*39777.15*	*0.80*	*46*	*22106.60*	*31871.93*	*0.78*	*51*	*32846.78*	*40082.56*	*0.55*
15	*74*	*34484.94*	*49427.81*	*0.51*	*48*	*25363.22*	*43234.70*	*0.50*	*64*	*31337.41*	*45367.52*	*0.73*
Average	*66.27*	*29465.05*	*38794.20*	*0.61*	*62.93*	*31734.70*	*40340.52*	*0.57*	*64.27*	*30385.70*	*40151.81*	*0.60*

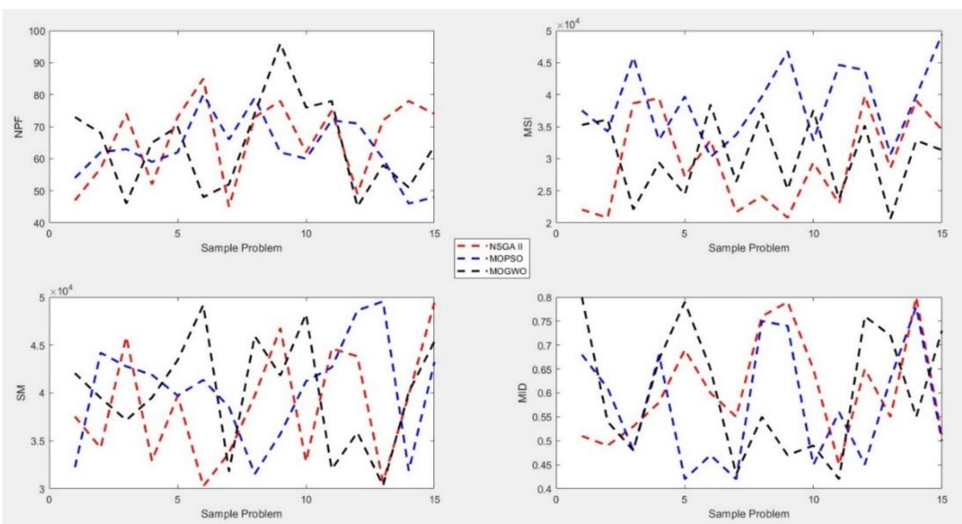

FIGURE 3
COMPARISON INDICES OF META-HEURISTIC ALGORITHMS IN SMALL TO LARGE SAMPLE SIZE PROBLEMS

According to the results of Table (6) and (7) and the examination of the overall averages of the comparison indices of meta-heuristic algorithms, it can be concluded that the NSGA II has obtained better results than other algorithms in obtaining the indices of the number of efficient solution and the spacing index. Also, the MOPSO has performed better in obtaining the indicators of the greatest expansion, the average computing time and the distance from the ideal point. Finally, the MOGWO has performed better than other algorithms in obtaining the averages of the first and second objective function. Due to the fact that different algorithms have shown their efficiency in obtaining different indices, TOPSIS method has been used to rank the algorithms.

TABLE 8
INDICES USED TO RANK ALGORITHMS

Algorithm	MOBF1	MOBF2	NPF	MSI	SM	MID	Cpu time
NSGA II	16981.36	7952.75	66.27	29465.05	38794.20	0.61	384.77
MOPSO	16932.89	8000.60	62.93	31734.70	40340.52	0.57	436.68
MOGWO	16967.66	7914.12	64.27	30385.70	40151.81	0.60	514.62
Preferred weight	0.25	0.25	0.1	0.1	0.1	0.1	0.1

The results of the implementation of the TOPSIS method for ranking algorithms for solving the problem of sustainable integrated production system include obtaining a desirability weight of 0.5882 for the MOPSO, obtaining a desirability weight of 0.1397 for the MOGWO, and obtaining a desirability weight of 0.7491 for the NSGA II. Therefore, the NSGA II can solve the problem of the designed integrated production system more efficiently than other proposed algorithms. In the following, the first problem of the designed sample is examined and the output variables of the problem are examined with the epsilon method of limitation. Therefore, before solving the problem, the best value of the first and second objective functions of the problem has been obtained by the individual optimization method. In this method, the optimal value of the first objective function is 5436.68 in a period of 67.15 seconds and the optimal value of the second objective function is 1080 in a period of 45.26 seconds.

TABLE 9
THE SET OF EFFICIENT SOLUTIONS RESULTING FROM SOLVING THE PROBLEM OF EXAMPLE 1

Efficient solutions	NSGA II			MOPSO			MOGWO			Epsilon Constraint		
	OBFV1	OBFV2	Cpu time	OBFV1	OBFV2	Cpu time	OBFV1	OBFV2	Cpu time	OBFV1	OBFV2	Cpu time
1	5599.72	2213	18.64	5777.11	2230	26.34	5590.25	2212	27.64	5474.93	2226	246.24
2	6664.01	2190		5857.13	2214		5604.30	2200		5493.87	2212	
3	6085.72	2147		5984.51	2190		5642.19	2176		5512.81	2190	
4	6123.66	2143		5996.10	2173		5828.28	2159		5541.97	2188	
5	6308.02	2129		6099.04	2164		5988.93	2156		6695.95	2109	
6	6557.17	2110		6207.78	2145		6095.07	2140		7136.41	2085	
7	6949.16	2087		6310.42	2107		6195.82	2127		8155.36	1967	
8	7380.31	2040		6542.79	2087		6233.26	2124		8174.30	1949	
9	7516.28	2037		6689.48	2074		6256.07	2118		9097.55	1890	
10	7937.23	1983		6766.37	2060		6319.93	2110		-	-	
11	8408.87	1952		7231.93	2018		6458.00	2088		-	-	
12	8555.64	1930		7507.42	2008		6856.27	2040		-	-	
13	-	-		8205.40	1956		7483.74	1993		-	-	
14	-	-		8484.71	1940		7892.29	1973		-	-	
15	-	-		8950.08	1915		8058.43	1950		-	-	
16	-	-		-	-		8250.81	1943		-	-	
17	-	-		-	-		8370.35	1930		-	-	
18	-	-		-	-		8991.02	1896		-	-	
Average	6948.82	2080.08	18.64	6840.49	2085.40	26.34	6789.72	2074.17	27.64	6809.24	2090.67	246.24

Fig. 4, and Table (8) also show the Pareto front obtained from solving the first sample problem and the set of efficient solutions obtained from solving this sample problem with the NSGA II, MOPSO, MOGWO and epsilon method.

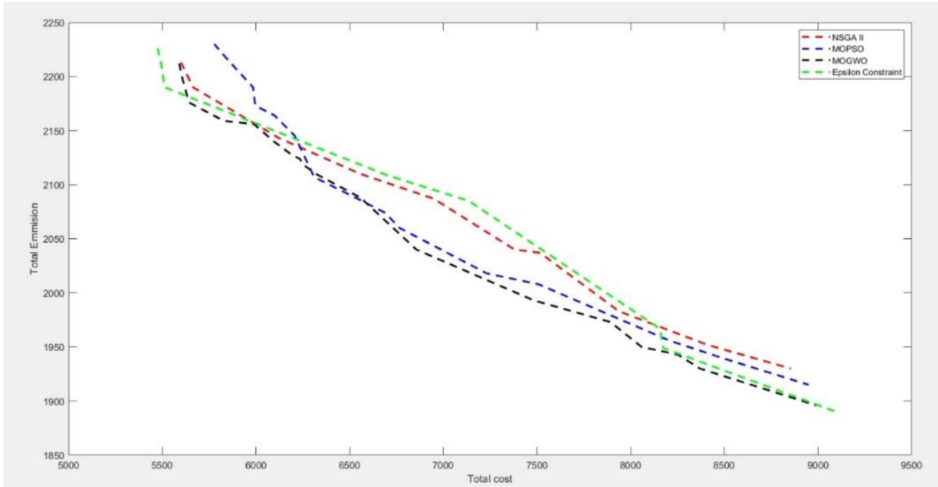

FIGURE 4
THE PARETO FRONT OBTAINED FROM SOLVING PROBLEM EXAMPLE 1

According to Fig. 4, it can be seen that with the increase in the costs of the entire production system, the amount of greenhouse gas emissions has decreased due to outsourcing. Also, based on this, the Epsilon method has 8 effective solution in 246.24 seconds, the MOGWO has 18 effective solution in 27.64 seconds, the MOPSO has 15 effective solution in 26.34 seconds, and finally the NSGA II has 12 effective solution in 18.64 seconds. Table (9) shows the total number of machines and the number of machines allocated to each cell. Table (10) also shows the level of discount applied for production outsourcing.

TABLE 10
THE NUMBER OF MACHINES ASSIGNED TO EACH CELL

	Cell 1	*Cell 2*	*Cell 3*	*Cell 4*	*Cell 5*	*Total number of machine*	*Usage rate*
Machine 1	-	-	-	*2*	-	*2*	*0.967*
Machine 2	-	-	*1*	-	-	*1*	*0.974*
Machine 3	-	-	*1*	-	*2*	*3*	*0.923*
Machine 4	*2*	*2*	-	-	-	*4*	*0.561*

TABLE 11
THE LEVEL OF DISCOUNT APPLIED TO THE PRODUCTION OF OUTSOURCED PARTS

Parts	*Scenario 1*			*Scenario 2*		
	Discount level 1	*Discount level 2*	*Discount level 3*	*Discount level 1*	*Discount level 2*	*Discount level 3*
Parts 1			*	*		
Parts 2			*		*	

According to the results of Table (10), it can be seen that in the first scenario for the outsourced production of the first and second parts, the discount level is 3, and in the second scenario, the discount level is 1 for the first part and the second discount level is applied for the second part. In this paper, according to the use of the robust-fuzzy-probabilistic optimization method to control the uncertainty parameters, the effect of the uncertainty rate on the values of the problem's objective functions in the fuzzy optimistic, fuzzy probable and fuzzy pessimistic states has been investigated. Table (11) shows the values of the objective functions in different rates of uncertainty. According to the results obtained from the sensitivity analysis, it can be seen that with the increase of the uncertainty rate in three optimistic, probable and pessimistic states, the amount of demand has decreased and therefore the value of the first objective function, which includes the costs of the entire production system, has decreased. . On the other hand, due to the effect of this problem on the amount of greenhouse gas emissions in the production and reproduction of products, the value of the second objective function has also decreased.

TABLE 12
THE TREND OF CHANGES OF THE FIRST AND SECOND OBJECTIVE FUNCTION IN DIFFERENT RATES OF UNCERTAINTY IN DIFFERENT STATES OF ROBUSTNESS

α_1	α_2	$\vartheta = 0$		$\vartheta = 0.5$		$\vartheta = 1$	
		Objective function 1	Objective function 2	Objective function 1	Objective function 2	Objective function 1	Objective function 2
0.1	*0.9*	*10724.26*	*3471*	*10006.82*	*3471*	*9343.27*	*3471*
0.2	*0.8*	*9514.17*	*3360*	*8956.65*	*3360*	*8443.43*	*3360*
0.3	*0.7*	*6860.94*	*2614*	*6493.30*	*2614*	*6154.39*	*2614*
0.4	*0.6*	*5684.56*	*2226*	*5474.93*	*2226*	*5284.82*	*2226*
0.5	*0.5*	*4945.12*	*1533*	*4019.57*	*1533*	*3963.77*	*1533*
0.6	*0.4*	*2964.92*	*1118*	*2532.92*	*1118*	*2116.92*	*1118*
0.7	*0.3*	*2822.92*	*1118*	*2248.92*	*1118*	*1826.41*	*1118*
0.8	*0.2*	*1680.92*	*1118*	*1564.92*	*1118*	*1240.36*	*1118*
0.9	*0.1*	*1538.92*	*1118*	*1380.92*	*1118*	*1138.14*	*1118*

Fig. 5. also shows the change process of the objective functions of the problem in different states of robustness (optimistic-probable and pessimistic) in different rates of uncertainty.

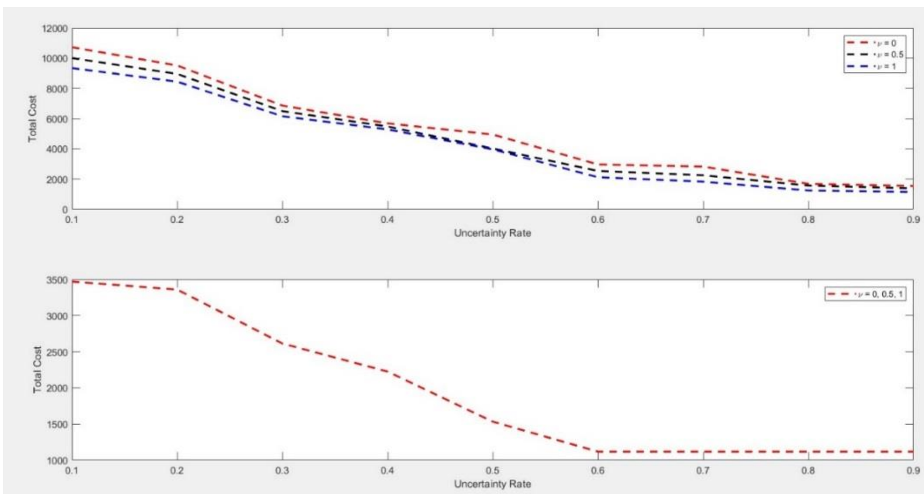

FIGURE 5
THE CHANGE PROCESS OF THE OBJECTIVE FUNCTIONS OF THE PROBLEM IN DIFFERENT STATES OF ROBUSTNESS

Comparing the results of different numerical examples solved with NSGA II, MOPSO, MOGWO and Epsilon constraint show that due to the NP-Hardness of the mathematical model, exact methods are not very effective in solving numerical examples. While the use of meta-heuristic methods has the ability to search the solution space of the model in a shorter time. The difference between the results obtained between different solution methods shows that the maximum GAP between these methods is less than 1%. While the time to solve the problem in exact methods is very high. Also, various comparisons have been made between different algorithms and their efficiency has been measured in terms of various indicators. In this comparison, NSGA II has the highest NPF and the lowest CPU-Time. MOPSO has been efficient in MSI and MID indices and finally MOGWO has won the best SM. Comparing all indicators at a glance shows that NSGA II is the most suitable solution method.

CONCLUSION

In this paper, a dual-objective model of a sustainable integrated production system was presented, taking into account the simultaneous reduction of possible costs on the system, the amount of greenhouse gas emissions, and the application of discounts on production outsourcing costs under uncertainty. Therefore, the robust-fuzzy-probabilistic optimization method (optimistic-pessimistic) was used to control the integrated production system model. The main goal in designing the model was to minimize the costs of the entire production system and minimize the amount of greenhouse gas emissions. To solve the model, the exact epsilon constraint method and MOPSO, NSGA II and MOGWO were used. To check the efficiency of the solution methods on the bi-objective model, 15 sample problems in small, medium, and large design sizes were used, and meta-heuristic algorithms comparison indices including the number of efficient solutions, maximum expansion, spacing, and distance from the ideal point were used.

As a result of the investigations, it was found that the exact method does not have a high efficiency in solving medium and large sample problems. However, the meta-heuristic algorithms of the average of the first and second objective function are closer than the averages of the epsilon method. According to the results and the analysis of the average indices of meta-heuristic algorithms comparison, it was concluded that the NSGA II has obtained better results than other algorithms in obtaining the indices of the number of efficient solution and the spacing index. Also, the MOPSO has performed better in obtaining the indicators of the greatest expansion, the average computing time and the distance from the ideal point. Finally, the MOGWO has performed better than other algorithms in obtaining the averages of the first and second objective function. The results of the implementation of the TOPSIS method for ranking algorithms for solving the problem of sustainable integrated production system included obtaining a desirability weight of 0.5882 for the MOPSO, obtaining a desirability weight of 0.1397 for the MOGWO, and obtaining a desirability weight of 0.7491 for the NSGA II.

The results of this article show that managers should choose high-tech machines in order to reduce the costs of their production unit and also to reduce the amount of harmful effects on the environment. Also, the influence of the uncertainty rate on the costs and environmental effects is shown in this article, and it leads to determine the minimum and maximum costs of setting up the production unit. On the other hand, creating an integrated production system network with countless decisions requires the use of special solution tools, which in this article, meta-heuristic algorithms have been developed for this purpose. The following are proposed as future proposals: considering the mathematical model in several periods and several products due to its closeness to the real world, considering different production technologies to reduce environmental effects, using innovative combined methods to achieve Favorable results in a short period of time, considering the reliability in the production system.

REFERENCES

[1] Alhourani, F. (2016). Cellular manufacturing system design considering machines reliability and parts alternative process routings. International Journal of Production Research, 54(3), 846-863.

[2] Arampantzi, C., & Minis, I. (2017). A new model for designing sustainable supply chain networks and its application to a global manufacturer. Journal of Cleaner Production, 156, 276-292

[3] Assid, M., Gharbi, A., & Hajji, A. (2020). Production control of failure-prone manufacturing-remanufacturing systems using mixed dedicated and shared facilities. International Journal of Production Economics, 224, 107549.

[4] Bayram, H., & Şahin, R. (2016). A comprehensive mathematical model for dynamic cellular manufacturing system design and Linear Programming embedded hybrid solution techniques. Computers & Industrial Engineering, 91, 10-29.

[5] Chan, F. T., Li, N., Chung, S. H., & Saadat, M. (2017). Management of sustainable manufacturing systems-a review on mathematical problems. International Journal of Production Research, 55(4), 1210-1225.

[6] Chu, C. H., & Tsai, M. (1990). A comparison of three array-based clustering techniques for manufacturing cell formation. The International Journal Of Production Research, 28(8), 1417-1433.

[7] Ćwikła, G., & Foit, K. (2017). Problems of integration of a manufacturing system with the business area of a company on the example of the Integrated Manufacturing Systems Laboratory. In MATEC Web of Conferences (Vol. 94, p. 06004). EDP Sciences.

[8] Dehnavi-Arani, S., Saidi-Mehrabad, M., & Ghezavati, V. (2019). An integrated model of cell formation and scheduling problem in a cellular manufacturing system considering automated guided vehicles' movements. International Journal of Operational Research, 34(4), 542-561.

[9] Ghahremani-Nahr, J., & Ghaderi, A. (2022). Robust-fuzzy optimization approach in design of sustainable lean supply chain network under uncertainty. Computational and Applied Mathematics, 41(6), 1-44.

[10] Ghanei, S., & AlGeddawy, T. (2020). An Integrated Multi-Period Layout Planning and Scheduling Model for Sustainable Reconfigurable Manufacturing Systems. Journal of Advanced Manufacturing Systems, 19(01), 31-64.

[11] Goli, A., Tirkolaee, E. B., & Aydın, N. S. (2021). Fuzzy integrated cell formation and production scheduling considering automated guided vehicles and human factors. IEEE transactions on fuzzy systems, 29(12), 3686-3695.

[12] Golpîra, H., Khan, S. A. R., & Zhang, Y. (2018). Robust smart energy efficient production planning for a general job-shop manufacturing system under combined demand and supply uncertainty in the presence of grid-connected microgrid. Journal of cleaner production, 202, 649-665.

[13] Jauhari, W. A., Pujawan, I. N., & Suef, M. (2021). A closed-loop supply chain inventory model with stochastic demand, hybrid production, carbon emissions, and take-back incentives. Journal of Cleaner Production, 320, 128835.

[14] Khezri, A., Benderbal, H. H., & Benyoucef, L. (2019, September). A sustainable reconfigurable manufacturing system designing with focus on environmental hazardous wastes. In 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA) (pp. 317-324). IEEE.

[15] KiA, R., Javadian, N., & Tavakkoli-Moghaddam, R. (2014). A simulated annealing algorithm to determine a group layout and production plan in a dynamic cellular manufacturing system. Journal of Optimization in Industrial Engineering, 7(14), 37-52.
[16] Liu, C., Tang, D., Zhu, H., & Nie, Q. (2021). A Novel Predictive Maintenance Method Based on Deep Adversarial Learning in the Intelligent Manufacturing System. IEEE Access.
[17] Lufika, R. D., & Meutia, S. (2021, February). The integrated lean and green manufacturing system: a case study at the peeled loaf production. In IOP Conference Series: Materials Science and Engineering (Vol. 1082, No. 1, p. 012010). IOP Publishing.
[18] Mohtashami, Z., Aghsami, A., & Jolai, F. (2020). A green closed loop supply chain design using queuing system for reducing environmental impact and energy consumption. Journal of Cleaner Production, 242, 118452.
[19] Nujoom, R., Mohammed, A., & Wang, Q. (2018). A sustainable manufacturing system design: a fuzzy multi-objective optimization model. Environmental Science and Pollution Research, 25(25), 24535-24547.
[20] Ojstersek, R., Acko, B., & Buchmeister, B. (2020). Simulation study of a flexible manufacturing system regarding sustainability. Int. J. Simul. Model, 19(1), 65-76.
[21] Rabbani, M., Farrokhi-Asl, H., & Ravanbakhsh, M. (2019). Dynamic cellular manufacturing system considering machine failure and workload balance. Journal of Industrial Engineering International, 15(1), 25-40.
[22] Rajak, S., Vimal, K. E. K., Arumugam, S., Parthiban, J., Sivaraman, S. K., Kandasamy, J., & Duque, A. A. (2022). Multi-objective mixed-integer linear optimization model for sustainable closed-loop supply chain network: a case study on remanufacturing steering column. Environment, Development and Sustainability, 24(5), 6481-6507.
[23] Raoofpanah, H., Ghezavati, V., & Tavakkoli-Moghaddam, R. (2019). Applying an Imperialist competitive algorithm for scheduling parts in a green cellular manufacturing system with consideration of production planning. Journal of Industrial and Systems Engineering, 12(3), 226-248.
[24] Sadeghi, A., Suer, G., Sinaki, R. Y., & Wilson, D. (2020). Cellular manufacturing design and replenishment strategy in a capacitated supply chain system: A simulation-based analysis. Computers & Industrial Engineering, 141, 106282.
[25] Salehi-Amiri, A., Zahedi, A., Gholian-Jouybari, F., Calvo, E. Z. R., & Hajiaghaei-Keshteli, M. (2022). Designing a closed-loop supply chain network considering social factors; a case study on avocado industry. Applied Mathematical Modelling, 101, 600-631.
[26] Sarkar, B., & Bhuniya, S. (2022). A sustainable flexible manufacturing–remanufacturing model with improved service and green investment under variable demand. Expert Systems with Applications, 202, 117154.
[27] Sharda, B., & Banerjee, A. (2013). Robust manufacturing system design using multi objective genetic algorithms, Petri nets and Bayesian uncertainty representation. Journal of Manufacturing Systems, 32(2), 315-324.
[28] Shirazi, H., Kia, R., Javadian, N., & Tavakkoli-Moghaddam, R. (2014). An archived multi-objective simulated annealing for a dynamic cellular manufacturing system. Journal of Industrial Engineering International, 10(2), 1-17.
[29] Tang, S., Wang, W., & Zhou, G. (2020). Remanufacturing in a competitive market: A closed-loop supply chain in a Stackelberg game framework. Expert Systems with Applications, 113655.
[30] Tavakoli, M. M., Haleh, H., & Mohammadi, M. (2018). A mathematical model for scheduling of production process and allocation of an automatic guided vehicle in a flexible manufacturing system. International Journal of Engineering Systems Modelling and Simulation, 10(2), 125-131.
[31] Tirkolaee, E. B., Mardani, A., Dashtian, Z., Soltani, M., & Weber, G. W. (2020). A novel hybrid method using fuzzy decision making and multi-objective programming for sustainable-reliable supplier selection in two-echelon supply chain design. Journal of Cleaner Production, 250, 119517.
[32] Utama, D. M., Santoso, I., Hendrawan, Y., & Dania, W. A. P. (2022). Integrated procurement-production inventory model in supply chain: a systematic review. Operations Research Perspectives, 100221.
[33] Yu, Z., & Khan, S. A. R. (2022). Green supply chain network optimization under random and fuzzy environment. International Journal of Fuzzy Systems, 24(2), 1170-1181.