A robust-fuzzy-probabilistic optimization model for the multi-objective problem of a sustainable green integrated production system under uncertainty

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Abstract

The design of a problem involving a sustainable integrated production system under uncertainty are covered in this article. The presented model aims to create an integrated production system that will lower costs across the board and greenhouse gas emissions. The robust-fuzzy-probabilistic (RFP) optimization method is used to control the non-deterministic parameters of the problem. The model's exact solution yielded calculation results that demonstrate that as greenhouse gas emissions have decreased, the production system's costs have increased as a result of changes in the number of machines and their technological capabilities. The outcome also demonstrates that as the uncertainty rate rises, the production system's level of demand also rises, which results in a rise in production. Costs and greenhouse gas emissions rise as a result of this increase in production. Additionally, the findings demonstrate that raising the average recycling rate improves the production system's stability. Because this is an NP-hard issue, many different optimization strategies have been tried, including the multi objective grey wolf optimizer (MOGWO) and the Non-dominated Sorting Genetic II (NSGA II). looking at the numerical examples of various sizes reveals that these algorithms have near-optimal solutions much more quickly and with much higher efficiency than the exact method.

Keywords: Green integrated production system, Robust-fuzzy-probabilistic optimization, multi objective grey wolf optimizer, Non-dominated Sorting Genetic II, greenhouse gas emissions

1. Introduction

Businesses have a major challenge in today's economy, and it has to do with the concept of sustainability. Though the concept of sustainability in the SC (SC) has received considerable attention in academic circles, the sustainable design of production systems has received less attention. For a manufacturing firm to be successful, a manufacturing system must work as a link in the SC. The vast customization possible with cellular production systems makes them a good choice for a long-term production infrastructure. Delivering a large variety of products and services to the marketplace that have been tailored to individual consumers' tastes is what is meant by the term "bulk customization" [1]. Mass customization is a strategy that combines the cost savings of transmission line or assembly production systems with the adaptability of process design systems like workshop production systems [2]. In the design of sustainable production systems, reproduction systems or combined reproduction-production systems can also be used due to the constructive effects of social, economic and environmental. Sustainability in production systems means reducing production costs, using maximum return products and reproducing products, and increasing social responsibility for increasing quality.

In today's competitive world, fulfilling the needs and orders of customers is not an easy task, changes in the amount of demand, type and size of demand have led to the production systems to step towards integration. In such systems, it is possible to produce products with high diversity in a shorter time. Therefore, due to the flexibility of such systems, production costs are also much lower [3]. In the SC, attention is not only to economic aspects, and therefore today production units also pay attention to environmental and social aspects. As a result, today's integrated production systems have moved towards sustainability and are trying to reduce the amount of environmental pollution in addition to reducing the production costs of various products and pay attention to social aspects such as human power. Putting together different aspects of sustainability and green in the integrated production system requires a comprehensive model design. In this research, due to the importance of producing diverse products with uncertain demand, the stability of the SC, as well as the recyclability of the product, a comprehensive model has been designed. The purpose of presenting the present model is to design a sustainable integrated production system under demand uncertainty, in which the optimal allocation of machines for the production of products is discussed and environmental and economic aspects are taken into account. Therefore, in addition to reducing the total production costs of the integrated system, the proposed model reduces the amount of greenhouse gas emissions caused by production. Integrated production system models are usually considered as hard problems. Therefore, in this research, the development of meta-heuristic algorithms (MHA) is also proposed to solve the problem. Therefore, the main research question can be stated as follows:

- What is the mathematical model of a sustainable integrated production system under uncertainty?

2- **Literature Review**

Hendalianpour and Razmi [4] came up with a one-of-a-kind approach to measuring the contentment of one's clients. In the proposed model, the customer feedbacks are considered to be linguistic terms because the evaluation criteria are shrouded in mystery and there is a lack of information regarding them. Since nonlinear interactions abound in human behavior and judgements, the output is generated using a fuzzy neural network. For the integrated production-distribution problem in a three-level SC including manufacturing, distribution hubs, and customers with a range of product kinds and throughout a variety of time periods, Vanaei et al. [5] created a mathematical model.

Darestani et al. [6] discussed a SC network for perishable goods that operates under uncertain conditions. They utilized the queue pattern in order to reduce the amount of time spent waiting in distribution centers. The simultaneous reduction in greenhouse gas emissions and overall network costs was one of the goals that their solution aimed to accomplish. Additionally, several model elements, including demand, operational expenses, freight prices, and the distribution center's approved capacity, were classified as uncertain parameters. Mohtashemi et al. [7] designed an environmentally friendly SC by utilizing forward and reverse logistics. They also used a queuing system to optimize the transportation and waiting time of the transport fleet network. Impacts on the environment are lessened by this optimization model. A supplier, a production system, a distribution center, a recycling center, a disposal center, and a collection center make up their suggested network. They take into account the total amount of production and load, and the solution that is suggested reduces the negative impact that transportation fleets have on the environment as well as the amount of energy that they use. This has an effect on the waiting times as well as the shipping times; in order to solve the problem, we used an MHA. Diabat et al. [8] proposed a reliable optimization model that took into account two different goals. Their approach takes into account both tactical and strategic options, and it aims to cut down on the amount of time and money needed to deliver products to customers. They suggested a strategy based on Lagrange release and the constraint as a way to effectively solve the two-objective model. Vahdani et al. [9] discussed the various location-inventory-pricing options available in a closed loop network. They also considered the requirements of the customers. They proposed an inventory strategy that included a variable delivery date, and they implemented a very inventive GA so that they could solve the problem. Gholizadeh et al. [10] presented a model for a SC that takes into account multiple objectives and is friendly to the environment. The proposed challenge has several aims, the most important of which are to cut overall costs, boost the efficiency of transportation methods, and cut down on information fraud committed by participants in the SC when information is shared with those participants. The foundational concept of nonlinear programming is represented by a complicated integer. They successfully implemented a fuzzy programming strategy. The recommended model employs a scenario-based stochastic approach to disturbance avoidance.

In the context of a production scenario involving a single machine, Ghaleb et al. [11] proposed a mathematical model that concurrently optimizes production scheduling and maintenance planning. The model determined the ideal maintenance action for each stage of deterioration, as well as the ideal inspection policy and work sequence, in order to accomplish the overriding goal of lowering the total cost as effectively as feasible. A GA that is efficient and is based on the features of the issue under investigation has been offered due to the complexity of the created model. A model based on game theory was developed by Hendalianpour [12] to account for the process by which retailers of perishable goods decide among themselves on pricing and lot size. Real-time scheduling (RTS) models were created by Ghaleb et al. [13] as a solution to the flexible job-shop scheduling problem (FJSP), which involves the introduction of unanticipated additional work in addition to the random breakdown of machines. He applied the Double Interval Grey Numbers in order to more accurately characterize customer behavior and to increase the quality of the analytical findings in real-world decision-making. This was done in order for him to accomplish both of these goals (DIGN). Liu et al. [14] investigated a two-tier SC that consisted of a standard retailer in addition to two competitors in the manufacturing sector. The maximization of overall profits at each and every stage of the SC is the fundamental purpose of the model that they have developed. This goal takes into consideration the stochastic demand, the costs that are connected with scarcity, as well as the holding charges. In accordance with a variety of different game theory tactics, they came to the conclusion that using Double Interval Grey Numbers (DIGN) would be the most effective method for determining the retail and wholesale pricing that would be most profitable. An integrated mathematical model for joint production scheduling and maintenance planning was suggested by Sharifi and Taghipour [15] for a deteriorating multi-failure single-machine manufacturing system. This model would be used when dealing with circumstances in which the machine would experience distinct phases of degradation. As a result of the intricacy of the model that was developed, the strategies of GA, SA, and TLBO have all been used in an effort to address the problem. A multi-product mathematical model was established by Liu and Hendalianpour [16], which makes it feasible to pick suppliers, manufacturing sites, distribution hubs, retail locations, and modes of transportation. The model takes into account both the material and the physical properties of the SC network as a whole in order to optimize the amount of money that can be earned via the network as a whole. In order to establish the ideal quantity of blood that should be delivered, the distribution method that should be applied, the inventory level that should be maintained, and the volume of products that should be moved between blood facilities, Liu et al. [17] constructed a mathematical model. In addition to this, in order to deal with the unpredictability of the demand from customers, they used a method of optimization that was resilient. Ghaleb et al. [18] have developed a method that may be used to create intelligent manufacturing systems that are capable of real-time integrated optimization of production scheduling and maintenance planning. By taking into consideration a variable job shop production structure and devising a solution for it, they were able to tackle a number of issues that typically arise in real operations.

Schroeder and Lodemann [19] conducted a research review on the previous work done on SC-related topics. They carried out a thorough literature review for this objective. The findings showed that in order to promptly address potential problems with the SC, the applicable examples largely relate to the early detection of risks in manufacturing, transportation, and supply. This was demonstrated by the findings. Nayal et al. [20] examined the challenges associated with using artificial intelligence and machine learning (AI-ML) to regulate the effects of COVID-19 in an Indian context while taking into account the agricultural SC (ASC). Review of the most recent research in the field of machine learning (ML) applied to the management of SCs and logistics, as given by Akbari and Do [21]. In order to carry out this review, an analysis of the current literature, contemporary ideas, facts, and gaps in the area was carried out.

In addition to that, they offered ideas for potential areas of research. According to the findings, 53.8% of the articles focused on the industrial and transportation sectors, while 54.7% of the articles concentrated on simulations and mathematical models. Zhu et al. [22] proposed a novel framework for demand forecasting that "borrows" time series data from numerous other products (cross-series training) and uses the data to train advanced machine learning models. This novel framework for demand forecasting can be found here. Hendalianpour et al. [23] came up with the idea of a multi-product distribution network as well as product shipping flows within the network despite the fact that the circumstances were unclear. To solve the problem posed by the suggested model, a novel strategy that combines Benders Decomposition (BD) and Lagrangian Relaxation has been developed. A distribution system, a sizeable e-commerce startup, and an online store are used in a case study that puts the model and approach for solving the problem into practice. A branch and bound (B&B) algorithm was proposed by Azimpoor et al. [24]. This algorithm limits search time and space, and it demonstrates how well inspection and maintenance operations can be integrated with job sequence. The goal of this research was to reduce expected makespan. Kosasih and Brintrup [25] proposed the problem of SC visibility as a link prediction problem in the context of machine learning (ML), and they suggest using a robotic method to find potential links that the buyer is unaware of using graph neural networks. This solution was proposed by Kosasih and Brintrup [25]. In addition, they discussed the advantages and disadvantages of utilizing GNN for link prediction and offered potential research topics for the researchers to look into in the future. The most important research is summarized in Table (1), and at the end of the table, the research gap that has been identified is stated:

Table 1. Summary of literature review

Considering the presented theoretical literature as well as reviewing the research literature, it can be stated that providing a model for an integrated green and sustainable production system considering the possible uncertain costs of the system is one of the necessities of any research. Therefore, in this article, the stability of the system is discussed under the title of using the maximum number of return products to reproduce new products.

As a result, the most important aspects of this article, including its contributions, may be summed up as follows:

- Designing a model of integrated green and sustainable production system

- Applying the RFP optimization method to control the non-deterministic parameters of the model
- Integration of optimistic and pessimistic fuzzy programming models in the proposed control method
- Using MHA in solving multi-objective models

In the following, the problem is described as well as the modeling of the problem in definite and controlled conditions.

3- Problem definition and modeling

In this paper, a model for an integrated green and sustainable production system is designed by considering the possible uncertain costs of the system. In this case, there are several different machines and several cells, twenty of each of which are assigned to related cells and process parts. Since not every machine has the ability to process all parts, assigning parts to machines is another category of problem decision. The parts processing process ultimately leads to the creation of a variety of products in the integrated production system and also the system returns part of the products produced to the system for recycling or disposal. Therefore, this process is subject to various costs of allocation, production, transportation, operations, etc., as well as the production and reproduction of parts and products in the integrated production system leads to greenhouse gas emissions. Therefore, the main purpose of this research is the optimal allocation of parts to machines for processing and also the optimal allocation of machines to each cell. In this article, some parts are outsourced in the production center and some parts are outsourced. Therefore, finding the amount of processable parts within the assembly or outsourcing the process is also one of the most important goals of the research.

The decrease of greenhouse gas emissions from the manufacturing and duplication of commodities, as well as the cost of the full integrated production system, are supplementary objective function (OBF)s of the issue. Since they are all assumed to be plausible and unpredictable in this study, the demand, operational expenses, transportation, and processing time. In order to solve the two-objective model and control non-deterministic parameters, the RFP optimization approach has been applied. The following assumptions may be used to describe the multi-objective system for an integrated green and sustainable production system by taking into account the system's potential unknown costs:

- The model under consideration aims to reduce both the quantity of greenhouse gas emissions and the overall cost of the manufacturing system.
- The trapezoidal shape of demand, operational expenses, transportation, and processing time is ambiguous and imprecise.
- In order to manage unknown parameters, a RFP optimization approach will be applied.
- It is a single-cycle and multi-product model.
- Production capacity is clear and definite.

3-1- Sets

I	Set of all kinds of parts
M	Machine set
C	Cell Set
J	Returned product Set
S	Set of scenarios

3-2- Parameters

$\tilde{D}_i^s$	Demand for each part i in scenario s
$\tilde{E}_i$	Production cost for each part i
$\tilde{W}_i$	Intracellular material transfer cost for each part i
$\tilde{T}_{im}$	Processing time of each part i on the machine m
σ_m	maintenance cost of machine m
ε_m	Buying cost of machine m
β_m	Operating cost of machine m
μ_m	Machine capacity m
L_c	Constraint for low-size of cell c
U_c	Constraint for high-size of cell c
ξ_i	Recycling rate per part i
γ_{im}	If part i is processed by machine m, it takes 1 and otherwise 0
O_i^s	The cost of outsourcing part i in scenario s
B_{ji}	Number of parts i used in the product j
$\varnothing_j$	Unit cost to get the returned product j
k_j	Start-up cost for dismantling the return product j
τ_j	Cost of dismantling the return product j
χ_j	Cost of destroying the returned product j
$MTBF_m$	The average time between two consecutive failures of machine m
$MTTR_m$	Average time between two consecutive repairs of machine m
Q_m	Breakdown cost for machine m
P_s	Probability of occurrence of scenario s
Co_{imc}	The amount of carbon dioxide emitted by processing an part i on machine m in cell c
C_j	Carbon dioxide emissions in disassembly of product j
G_{mc}	The rate of carbon dioxide emissions at the start of machine m in cell c

3-3- Decision variables

λ_{imc}^s	The rate of entry of part i on machine m in cell c in scenario s
Q_i^s	Outsourcing the part i in scenario s

Z^{s}_{imc}	If part i is processed on machine m in cell c in scenario s it gets 1 and otherwise it gets 0.
N_{mc}	Number of machines m used in cell c
ζ_m	Number of machines m to be purchased
ρ_m	usage rate of machine m
d_j	Number of returned products j for disassembly
r_j	Number of returned products j to be obtained
δ_j	If the return product j is dismantled, it takes 1 and otherwise 0.
α_{mc}	If machine m is assigned to cell c, it takes 1 and otherwise 0.
X_{ic}	If part i is processed in cell c, it gets a value of 1 and otherwise 0.

Two-objective model of integrated production system in conditions of uncertainty

$$minZ_1 = E\left[Z\right] + \xi\left(Zmax - Zmin\right) + \omega\sum_{s} P_s\left\{E\left[Z\right] - E\left[Z_s\right] + 2\theta_s\right\} + \eta_1\sum_{i}\sum_{s} P_s\left[D_i^{s-4} - \frac{\left(\alpha_s - \lambda\right)D_i^{s(3)} + \left(1-\alpha_s\right)D_i^{s(3)}}{1-\lambda}\right] \tag{1}$$

$$minZ_2 = \sum_{s}\sum_{i}\sum_{m}\sum_{c} P_s.Co_{imc}.\lambda^{s}_{imc} + \sum_{j} C_j.d_j + \sum_{m}\sum_{c} G_{mc}.N_{mc} \tag{2}$$

Minimizing the costs of the complete integrated production system, including production expenses, equipment purchases, processing costs, transportation costs, and so on, is included in Equation (1).

The minimization of greenhouse gas emissions from the manufacturing and replication of goods and components is shown in Equation (2). According to the aforementioned OBF, the following are the model's constraints:

$$Q_i^s + \sum_{m}\sum_{c}\lambda^{s}_{imc} = \left[\left(1-\nu_1\right)\left[\left(1-\alpha_s\right)D_i^{s(3)} + \alpha_s D_i^{s(4)}\right] + \left(\nu_1\right)\left[\left(1-\alpha_s\right)D_i^{s(1)} + \alpha_s D_i^{s(2)}\right]\right], \forall i, s \tag{3}$$

$$\begin{aligned} Zmin = {} & \sum_{s}\sum_{i}\sum_{m}\sum_{c} P_s.T^{1}_{im}.\lambda^{s}_{imc}.\beta_m.\left(1+\frac{MTTR_m}{MTBF_m}\right) + \\ & \sum_{s}\sum_{i}\sum_{m}\sum_{c} P_s.T^{1}_{im}.\frac{\lambda^{s}_{imc}}{MTBF_m}.Q_m + \sum_{i}\sum_{s} P_s.O_i^s.Q_i^s + \sum_{s}\sum_{i}\sum_{m}\sum_{c} P_s.E_i^1.\lambda^{s}_{imc} \\ & \sum_{i}\sum_{m}\sum_{c} W_i^1.\gamma_{im}.X_{ic} - \sum_{i}\sum_{m}\sum_{c} W_i^1.\gamma_{im}.F_{icm} + \sum_{m}\sum_{c}\sigma_m.N_{mc} + \sum_{m}\varepsilon_m.\zeta_m + \\ & \sum_{j}\varnothing_j.r_j + k_j.\delta_j + \tau_j.d_j + \sum_{j}\sum_{i}\left(1-\xi_i\right).\chi_j.B_{ji}.d_j \end{aligned} \tag{4}$$

$$Zmax = \sum_s \sum_i \sum_m \sum_c P_s . T_{im}^4 . \lambda_{imc}^s . \beta_m . \left(1 + \frac{MTTR_m}{MTBF_m}\right) +$$

$$\sum_s \sum_i \sum_m \sum_c P_s . T_{im}^4 . \frac{\lambda_{imc}^s}{MTBF_m} . Q_m + \sum_i \sum_s P_s . O_i^s . Q_i^s + \sum_s \sum_i \sum_m \sum_c P_s . E_i^4 . \lambda_{imc}^s \quad (5)$$

$$\sum_i \sum_m \sum_c W_i^4 . \gamma_{im} . (X_{ic} - F_{icm}) + \sum_m \sum_c \sigma_m . N_{mc} + \sum_m \varepsilon_m . \zeta_m +$$

$$\sum_j \varnothing_j . r_j + k_j . \delta_j + \tau_j . d_j + \sum_j \sum_i (1 - \xi_i) . \chi_j . B_{ji} . d_j$$

$$E[Z_s] = \sum_c \sum_i \sum_m \left[\left(\frac{1-\lambda}{2}\right)\left(T_{im}^1 + T_{im}^2\right) + \left(\frac{\lambda}{2}\right)\left(T_{im}^3 + T_{im}^4\right)\right] . \lambda_{imc}^s . \beta_m . \left(1 + \frac{MTTR_m}{MTBF_m}\right)$$

$$+ \sum_c \sum_i \sum_m \left[\left(\frac{1-\lambda}{2}\right)\left(T_{im}^1 + T_{im}^2\right) + \left(\frac{\lambda}{2}\right)\left(T_{im}^3 + T_{im}^4\right)\right] . \frac{\lambda_{imc}^s}{MTBF_m} . Q_m + \sum_i O_i^s . Q_i^s +$$

$$\sum_c \sum_i \sum_m \left[\left(\frac{1-\lambda}{2}\right)\left(E_i^1 + E_i^2\right) + \left(\frac{\lambda}{2}\right)\left(E_i^3 + E_i^4\right)\right] . \lambda_{imc}^s + \sum_m \sum_c \sigma_m . N_{mc} + \sum_m \varepsilon_m . \zeta_m \quad (6)$$

$$+ \sum_i \sum_m \sum_c \left[\left(\frac{1-\lambda}{2}\right)\left(W_i^1 + W_i^2\right) + \left(\frac{\lambda}{2}\right)\left(W_i^3 + W_i^4\right)\right] . \gamma_{im} . (X_{ic} - F_{icm}) +$$

$$\sum_j \varnothing_j . r_j + k_j . \delta_j + \tau_j . d_j + \sum_j \sum_i (1 - \xi_i) . \chi_j . B_{ji} . d_j , \ \forall s$$

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

$$\sum_s \sum_i \sum_m \sum_c P_s . \left[\frac{T_{im}^1 + T_{im}^2 + T_{im}^3 + T_{im}^4}{4}\right] . \frac{\lambda_{imc}^s}{MTBF_m} . Q_m + \sum_i \sum_s P_s . O_i^s . Q_i^s +$$

$$\sum_s \sum_i \sum_m \sum_c P_s . \left[\frac{E_i^1 + E_i^2 + E_i^3 + E_i^4}{4}\right] . \lambda_{imc}^s + \sum_m \sum_c \sigma_m . N_{mc} + \sum_m \varepsilon_m . \zeta_m + \quad (7)$$

$$\sum_i \sum_m \sum_c \left[\frac{W_i^1 + W_i^2 + W_i^3 + W_i^4}{4}\right] . \gamma_{im} . (X_{ic} - F_{icm}) + \sum_j \varnothing_j . r_j + k_j . \delta_j + \tau_j . d_j + \sum_j \sum_i (1 - \xi_i) . \chi_j . B_{ji} . d_j$$

The conclusion drawn from Equation (3) is that either in-house manufacturing or outsourcing will be used to satisfy the demand for each and every item under consideration. In this equation, demand is treated as a parameter that is subject to uncertainty. The relations (4) to (7) show the equations related to the RFP method. Therefore, the parameter ξ is the OBF's weight coefficient, η_1 is the cost of the penalty for underestimating demand, and η_2 is the function of the penalty for exceeding the facility's capacity. The coefficients of adjustment in the value of fuzzy surfaces of numbers are represented by the parameters α_s, β_s, which should have a value between 0.5 and 1.

$$Z_{imc}^s \le \gamma_{im} , \ \forall i, m, c, s \quad (8)$$

$$\lambda_{imc}^{s} \le BigM .Z_{imc}^{s}, \ \forall i, m, c, s \tag{9}$$

Equation (8) ensures that the processing of parts by machines is based on the processing capability of each machine. Equation (9) indicates that parts will be processed by the machine if the machine is dedicated to processing the part.

$$\sum_{i} T_{im} .\lambda_{imc}^{s} \le \mu_{m} .N_{mc}, \ \forall m, c, s \tag{10}$$

Equation (10) ensures that parts processing should not exceed the capacity of the machines.

$$L_{c} \le \sum_{m} N_{mc} \le U_{c}, \ \forall c \tag{11}$$

$$\sum_{c} N_{mc} \le \zeta_{m}, \ \forall m \tag{12}$$

In terms of the total number of machines that are allotted to each cell, Equation (11) ensures that there is no more than one upper limit and one lower limitation that may be reached at any one time. Equation (12) guarantees that the overall number of machines in the cell will be lower than the overall number of machines that have been bought.

$$\sum_{i}\sum_{c}\sum_{s} \frac{\lambda_{imc}^{s}}{\mu_{m}} = \rho_{m}, \ \forall m \tag{13}$$

$$\rho_{m} \le 1, \ \forall m \tag{14}$$

Equation (13) calculates and shows the productivity of each machine. Equation (14) ensures that the utilization rate of the machines should be less than 1.

$$\sum_{m}\sum_{c}\sum_{s} \lambda_{imc}^{s} \le \xi_{i} \sum_{j} B_{ji} .d_{j}, \ \ \forall i \tag{15}$$

$$r_{j} \ge d_{j}, \ \ \forall j \tag{16}$$

$$d_{j} \le BigM .\delta_{j}, \ \ \forall j \tag{17}$$

The total number of goods that were sent back is represented by the equation (15). Equation (16) calculates the number of products to be dismantled. Equation (17) ensures that the product must be dismantled before it is selected.

$$N_{mc} \le BigM .\alpha_{mc}, \ \ \forall m, c \tag{18}$$

$$\alpha_{mc} \le N_{mc}, \ \ \forall m, c \tag{19}$$

Equations (18) and (19) show how machines are assigned to each cell.

$$\sum_{m}\sum_{s} Z_{imc}^{s} \le BigM .X_{ic}, \ \ \forall i, c \tag{20}$$

$$\sum_{m}\sum_{s} Z_{imc}^{s} \ge X_{ic}, \ \ \forall i, c \tag{21}$$

Equations (20) and (21) show how each piece is assigned to the corresponding machine and cell.

$$F_{icm} \leq X_{ic}, \quad \forall i, m, c \tag{22}$$

$$F_{icm} \leq \alpha_{mc}, \quad \forall i, m, c \tag{23}$$

$$X_{ic} + \alpha_{mc} - F_{icm} \leq 1, \quad \forall i, m, c \tag{24}$$

$$\sum_{s} Z_{imc}^{s} = F_{imc}, \quad \forall i, m, c \tag{25}$$

Relationships (22) to (25) are constraints on model linearization.

$$\lambda_{imc}^{s}, Q_i^s, N_{mc}, \zeta_m, d_j, r_j \geq 0 \textit{ and integer} \tag{26}$$

$$Z_{imc}^{s}, \rho_m, \delta_j, \alpha_{mc}, X_{ic} \in \{0,1\} \tag{27}$$

Equations (26) and (27) show the type of decision variables.

4- Solving methods

4-1- MOGWO

Gray wolves are the top predators in both the food pyramid and the food chain. The vast majority of gray wolves choose to make their home in groups known as packs. The male and female members of the leadership team are both referred to as alphas. The majority of the decisions regarding activities such as hunting, where to sleep, when to get up, and other pursuits are made by Alpha. Choices made by the Alpha are communicated to the group, but there have been examples of democratic behavior in which an Alpha simply follows the lead of the other wolves in the pack. In a group, those who hold the position of Alpha have the backing of the whole herd. The dominant wolf is another name for the alpha wolf. This is due to the fact that the orders given by the alpha wolf must be carried out by the entire pack. Both the food pyramid and the food chain place gray wolves at the apex of the predatory food chain. The great majority of gray wolves live their whole lives in family-like groupings that are referred to as packs. The members of the leadership team, whether they are male or female, are collectively referred to as alphas. Alpha is the one who makes the bulk of the choices on activities like as hunting, where to sleep, when to get up, and other interests. The group is informed of the decisions made by the Alpha, although there have been documented cases of democratic conduct in which the Alpha merely follows the example set by the other wolves in the pack. Those members of a group who are able to maintain their status as Alpha enjoy the support of the whole herd. The term "alpha wolf" may also be referred to by the term "dominant wolf." This occurs as a result of the fact that the whole pack is obligated to carry out the commands that are issued by the alpha wolf. At no point in time are the alpha wolves permitted to mate with wolves from outside the herd. It is necessary to keep in mind that the Alpha is not always the member of the herd that boasts the most physical prowess, but rather the one who is the most skillful in terms of being able to govern the herd. This fact is especially important to keep in mind when dealing with large herds. Beta is the name given to the social position held by gray wolves that follows Alpha in the hierarchy of their pack. When it comes to making choices for the herd, Beta are the wolves who supply Alpha with counsel and aid in the form of both advice and assistance. The greatest potential substitute for the Alpha wolf would be the Beta wolf, who, depending on the circumstances, may be a male or a female. This would be the case even if the Alpha wolf were to die of old age or for some other cause. Beta is in charge of ensuring that Alpha's instructions are carried out across the herd and giving feedback to Alpha on their effectiveness. According to the hierarchy established by the gray wolf pack, the Omega wolf holds the position of the lowest ranked member of the pack. In this metaphor, the omega wolf functions as a stand-in for the victim. There are several situations in which omega wolves are compelled to defer to the authority of wolves that are more powerful and dominating. They are the only wolves who have survived to this day that are able to eat food. When a wolf does not fit into either of these two categories, we refer to it as a Delta. The Deltas are considered to be in the center of the pack. It is essential for the Alpha and Beta wolves to continue to exert their dominance over the Delta pack. Despite this, they are the ones that exercise authority over Omega. Alpha is believed to be the most suitable choice when seeking to develop the GWO in order to statistically describe the social hierarchy of wolves. This is because the GWO was designed to do just that. Therefore, the two replies that are considered to be the second and third most acceptable choices are beta and delta. It has been concluded that Omega is the answer after examining the other options that are still available. The gray wolf must first recognize its target before being able to properly hunt it and must then surround the animal. In order to create an updated position for the wolves in relation to the prey that they are seeking, the following equations are employed.

$$\vec{D} = \left| \vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t) \right| \tag{28}$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A}.\vec{D} \tag{29}$$

$\vec{C}$ and $\vec{A}$ are coefficient vectors in the aforementioned equations. The hunting position vector is ($\overrightarrow{X_p}$), while the gray wolf position vector is ($\vec{X}$). This is a siege and hunting equilibrium equation. As a result, throughout the procedure, the search radius must be optimized. The formulae for the two coefficients utilized in the aforementioned relations are as follows for this purpose.

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{30}$$

$$\vec{C} = 2\overrightarrow{r_2} \tag{31}$$

The aforementioned equations let gray wolves adjust their location in relation to their prey. As a consequence, the search is carried out using the following equations.

$$\begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1.\vec{X}_\alpha - \vec{X} \right| \\ \vec{D}_\beta &= \left| \vec{C}_2.\vec{X}_\beta - \vec{X} \right| \\ \vec{D}_\delta &= \left| \vec{C}_1.\vec{X}_\delta - \vec{X} \right| \end{aligned} \tag{32}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta \end{aligned} \tag{33}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{34}$$

The MOGWO pseudo-code is shown in Figure 1.

Figure 1. MOGWO pseudo-code algorithm

4-2- Torabi Hassini (TH) method

This innovative approach to tackling multi-objective problems was put out by Torabi et al. [44] The worst value of each OBF must also be obtained from the individual optimization approach in order to employ this method, in addition to the best value of each OBF. This approach aims to reduce the gap between the OBF' actual values and their ideal values.

- ***Step 1- Get the best and worst value of each OBF***

$$w_1^{NIS} = w_1\left(x_2^{PIS}\right),\ w_2^{NIS} = w_2\left(x_1^{PIS}\right) \tag{35}$$

- ***Step 2 - Define a linear membership function for each OBF:***

$$\mu_1(x) = \begin{cases} 1 & if \quad w_1 < w_1^{PIS} \\ \dfrac{w_1 - w_1^{PIS}}{w_1^{NIS} - w_1^{PIS}} & if \quad w_1^{PIS} \le w_1 \le w_1^{NIS} \\ 0 & if \quad w_1 > w_1^{NIS} \end{cases} \tag{36}$$

$$\mu_2(x) = \begin{cases} 1 & if \quad w_2 < w_2^{PIS} \\ \dfrac{w_2 - w_2^{PIS}}{w_2^{NIS} - w_2^{PIS}} & if \quad w_2^{PIS} \le w_2 \le w_2^{NIS} \\ 0 & if \quad w_2 > w_2^{NIS} \end{cases} \tag{37}$$

- ***Step 3- Use the following equation to integrate the OBFs***

$$Min\ \vartheta(x) = \varphi\vartheta_0 + (1-\varphi)\sum_{g=1}^{P} w_g \mu_g(x) \tag{38}$$

s.t.:

$$\vartheta_0 \le \mu_g(x),\ \forall\ g = 1,2 \tag{39}$$

$$x \in F(x),\ \vartheta_0\ and\ \vartheta \in [01] \tag{40}$$

Where φ is equal to the compensation coefficient of the OBFs and μ indicates the degree of effectiveness of the p -th of the OBF and the sum of the weights of the OBFs must also be equal to one.

Considering the dual purpose of the mathematical model in this article, TH method and MHAs have been used to determine efficient solutions and form the Pareto front. As a result, due to the existence of different effective solutions, indicators such as number pareto front (NPF), Maximum spread index (MSI), Space metric (SM), Mean of ideal deviations (MID) and CPU-Time have been used. Using these indicators, the efficiency of different methods can be checked ([46]).

5- Analysis of experiments

Using 2 parts, 5 cells, 6 machines, 2 products, and 2 alternative circumstances, a tiny sample problem is examined in this section. Since the model is considered in uncertain terms, the value of $\lambda = 0.5$ ، $\alpha_1 = 0.$ ، and $\alpha_2 = 0.6$ is assumed to control the problem parameters. Additionally, as real-world data is not readily available, random data produced as shown in Table (2) has been employed.

Table 2. Range of parameters generated for small and large sample size problems

According to equations (48) and (49), in order to create the Pareto front using the TH approach, it is necessary to acquire the greatest possible OBFV utilizing the individual optimization method. This is the case in order to produce the Pareto front. As a result, the reward table as well as 11 efficient solutions developed by the TH technique in accordance with random weights in 20 replications of the Monte Carlo method are shown in Table 3, which is located below the payoff table.

Table 3. Payoff table of effective solutions stemming from a passion for solving little problems

According to the analysis of the results, 11 efficient solutions have been obtained by the exact TH method. Also, the Pareto front obtained from this method is described in Figure (2). It can be seen that according to the results, with the increase of the costs of the integrated production system, the amount of greenhouse gas emissions has decreased. The reason for this is the use of high-production and high-cost machines, as well as lower greenhouse gas emissions.

Figure 2. Pareto front as a consequence of using the TH approach

The output variables are presented below for one of the effective solutions. As a result, Table (4) displays the overall machine count as well as the machine count for each cell. Along with its integrated production, Table (5) also lists the quantity of components allotted to each machine and cell.

Table 4. Each cell's assigned Machin number

Table 5. Number of parts allocated to each machine and cell for production along with the amount of production in each scenario

Also, in this problem, 21 products of the first type and 23 products of the second type have been returned to the system for reproduction and disassembly. In the following, the sensitivity at different uncertainty rates are analyzed.

Since the Pareto front obtained in the previous section is analyzed with the assumption $\lambda = 0.5$. Next, the value of λ changes in the range of 0.1 to 0.9 and the changes in the mean OBFVs for different rates of λ are shown in Figure (3).

Figure 3. The pattern of shifting OBF signifies in exchange for shifting rate λ

Figure (3) shows that when λ increases, demand shifts from optimistic (less demand) to pessimistic (higher demand). As demand rises in the integrated manufacturing system, production and machine costs rise. Greenhouse gas emissions rise with product demand and production. Also, on the other hand, the uncertainty rate in this problem was considered equal to 0.4 in each scenario. In order to better analyze the problem by increasing the uncertainty rate in each scenario, the obtained OBFVs are shown in Table (6) and Figure (4).

Table 6. The values of the OBFs of the problem under various degrees of uncertainty

Table (6) shows that when uncertainty rises in the first scenario, product demand rises, increasing manufacturing and transportation costs. Product manufacture has also raised greenhouse gas emissions. According to the results shown in Table 6, there is an increase in costs associated with both the second and first scenarios when the level of uncertainty is raised. Thus, if each scenario's demand is gloomy, the integrated production system's costs and greenhouse gas emissions would rise.

Figure 4. Differential uncertainty in OBFs.

In another analysis, changes in the average recycling rate in the integrated production system have been investigated. In this analysis, the average recycling rate is considered to be 0.3. By changing this parameter, the amount of reuse of products changes and leads to changes in the OBFs of the problem. Table (7) demonstrates how the OBFs vary with the average recycle rate.

Table 7. Different recycling rates' OBFs

The results of table (7) show that with the increase in the average recycling rate, the possibility of reusing returned products has increased and this has led to a reduction in the production costs of new products and a reduction in the amount of greenhouse gas emissions. Therefore, as much as you can use the returned products as much as possible, you can increase the sustainability of the integrated production system. the changes of the OBFs in different recycling rates is shown figure (5).

Figure 5. Differential recycling rate in OBFs.

5-1- small size sample problem

The small sample size problem is addressed using the NSGA II and MOGWO to examine and assess them. The comparative indicators of efficient solutions and the Pareto front from solving three techniques are displayed. According to the indices from NSGA II and MOGWO, TH technique is the most efficient way for getting MOBFV2 and MID in small sample problems. The NSGA II was best for MOBFV1 and MSI, and the MOGWO method for NPF, SM, and CPU-Time. Figure (6) illustrates the Pareto front from addressing small sample problems using various strategies.

Figure 6. Pareto front from addressing small sample issues using diverse strategies.

Figure (6) indicates that MHAs produce a fairly similar Pareto front to the precise technique. In this study, when the first OBF increases, the second OBF decreases.

4-2- larger sample sizes

The data in Table 1 inspired the following 15 larger sample problems (2). MOGWO and NSGA II ran each larger sample problem five times. Table 1 shows each performance indicator's average (8).

Table 8. Average indicators for comparing efficient solutions

Table (8) shows NSGA II and MOGWO OBF means and MHA comparison indices for each sample issue. T-Test at 95% confidence level compared results. Thus, Rejection of zero is rejected if the P test statistic for each index is less than 0.05, while Hypothesis one is rejected if it is more than 0.95.

5-3- T-Test on the means of OBFs and comparison indicators

Table (9) provides the T-Test outcome on OBF means and comparison indices.

Table 9- T-Test results on OBFs and computational indices

The means of the OBFs and MHA comparison indices do not vary substantially from one another, as shown by Table (9) and the P-value. Therefore, several multi-criteria decision-making strategies have to be employed in order to choose the algorithm that is going to be the most effective for comparable indicators. The comparison of the means of OBFs and comparison indices for MHA sample issues may be seen both below and in Figure (7).

Figure 7. Comparison of averages of OBFs and comparison indices

Figure (7) shows that computing time grows exponentially with sample problem size, making the task NP-Hard. The MOGWO method is faster than the NSGA II for medium-sized problems, but as the problem size increases, so does its processing time.

In the previous section, significant comparisons were made to identify the significant difference between the averages of the computational index acquired by solving the sample problems using NSGA II and MOGWO. These comparisons were done in order to determine whether or not the difference is statistically significant. According to the data, none of the initially estimated indices were substantially different from one another. In this part of the article, TOPSIS was used to choose the algorithm that was the most effective. After scaling, the MOGWO gained 0.9675 grams, which is an indication of how efficient it is.

6. Conclusion

The purpose of this piece of study is to offer a dual-objective green model for an integrated manufacturing system. The model takes into consideration both the simultaneous reduction of possible costs to the system and the quantity of greenhouse gas emissions under uncertainty.

The RFP optimization approach was consequently utilized as a means of controlling the integrated production system model. The use of this strategy has been shown to be very successful in achieving the goal of regulating unpredictable parameters in any circumstance. The recently established model is successful in both lowering the amount of emissions of greenhouse gases and lowering the expenses connected with the manufacturing system. In order to produce, classify, and allocate machines to each cell in order to produce the Pareto front and study the output variables of the problem, including the allocation of parts to machines, accurate TH methods are utilized when the size of the problem is small, whereas super-innovative NSGA II and MOGWO are utilized when the size of the problem is large.

This is done in order to manufacture, categorize, and distribute machines to each individual cell. When the numerical results and the obtained Pareto front were analyzed, it was found that the value of the problem's first OBF rises as the problem complexity rises, but the value of the problem's second OBF falls as the problem complexity rises. This was discovered by the fact that the value of the problem's second OBF decreases as the problem complexity rises. This shows that in order to reduce the amount of greenhouse gas emissions, it is required to deploy equipment that has a high rate of production and employs technology that is both up to date and pricey. Only then will it be possible to reduce the amount of greenhouse gas emissions.

Because of this, there will be an increase in the costs that are connected with the integrated production system as a direct consequence of this. The findings of the calculations also demonstrated that the quantity of product demand grew as the rate of uncertainty in the production system increased. This, in turn, led to a rise in the quantity of production as a direct consequence of the increase in product demand. An increase in the amount of output leads to a rise in the expenses of manufacturing and transportation, in addition to a rise in the quantity of greenhouse gas emissions. In the meantime, the sensitivity analysis that was performed on the recycling rate revealed that an increase in the recycling rate in the production system results in a greater amount of use of returned products and a smaller amount of production of new products. This was discovered as a result of the discovery that an increase in the recycling rate in the production system results in the production of new products.

This is the inference that can be made from the investigation on the effects of increasing the recycling rate. As a direct result of this, there will be a reduction in both the financial cost and the overall amount of emissions of greenhouse gases. As a consequence of this, MHAs were able to accomplish almost ideal outputs with a high degree of efficiency in the context of challenges of limited scope. As a direct result of this, 15 example problems with increasing sizes were produced and made available for review. Several other indices, such as the mean efficient solution, the number of efficient solutions, the maximum expansion, the metric distance, the distance from the ideal point, and the amount of computing time, were used to evaluate the efficacy of the MHAs.

In addition, the results of the statistical study showed that there was not a visible difference between the respective means of the computational indicators. This was one of the findings. As a consequence of this, the MOGWO was selected as the solution that would be the most successful in addressing the issue of integrated production systems. The results of this research suggest that managers of manufacturing units should place a primary priority on discovering new methods to reuse things that have been returned to them. Because the data suggest that increasing the rate of recycling leads in a reduction in the total expenditures of the integrated production system, a reduction in the amount of pollution, and, as a consequence, an improvement in the sustainability of the production system. The quick increase in demand that occurs as a direct consequence of an increase in production also leads to an increase in the total amount of money spent as well as the total quantity of greenhouse gas emissions. As a direct consequence of this, managers have the opportunity to prevent an increase in their expenditures by first planning and then establishing a product maintenance system that is adaptable to a variety of time periods. Because of the research that was carried out, a model has been developed that provides managers with assistance in finding a good balance between economic and environmental factors. Because of this, these managers are in a better position to make decisions that are consistent with the tasks they have been given.

In the interest of further research, it is suggested that the social aspects of the sustainability of the production system be taken into consideration. In addition to the economic and environmental aspects, it is also suggested that the problem of the amount of employment created in the production units be addressed. In addition, dependability in the production of items is not taken into account in this research, despite the fact that it has a significant impact on total costs on account of the manner that it influences total costs. As a consequence of this, it is strongly suggested that an investigation of the dependability of the model that was provided be conducted. In addition, one of the suggestions that can be made as a result of the results of the research is the development of hybrid methods for the solution of issues. This is one of the recommendations that can be made.

References

[1] Nagar, D. Raghav, S. Bhardwaj, A. Kumar, R., et al."Machine learning: Best way to sustain the SC in the era of industry 4.0", *Materials Today: Proceedings*, **47**, pp. 3676-3682 (2021).

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

[3] Malviya, L. Shreemali, J. Ojha, R., et al. "WITHDRAWN: Transformer prediction in the supply chain using machine learning", *Materials Today: Proceedings*, (2021).

[4] Hendalianpour, A. and Razmi, J. "Customer satisfaction measurement using fuzzy neural network", *Decision Science Letters*, **6**(2), pp. 193-206 (2017).

[5] Vanaei, H. Sharifi, M. Radfar, R., et al. "Optimizing of an Integrated Production-Distribution System with Probabilistic Parameters in a Multi-Level SC Network Considering the Backorder", *Journal of Operational Research in its Applications (Applied Mathematics)-Lahijan Azad University*, **16**(3), pp. 123-145 (2019).

[6] Darestani, S. A. and Hemmati, M. "Robust optimization of a bi-objective closed-loop SC network for perishable goods considering queue system", *Computers & Industrial Engineering*, **136**, pp. 277-292 (2019).

[7] Mohtashami, Z. Aghsami, A. and Jolai, F. "A green closed loop SC design using queuing system for reducing environmental impact and energy consumption", *Journal of Cleaner Production*, **242**, pp. 118452 (2020).

[8] Diabat, A. Jabbarzadeh, A. and Khosrojerdi, A. "A perishable product SC network design problem with reliability and disruption considerations", *International Journal of Production Economics*, **212**, pp. 125-138 (2019).

[9] Vahdani, B. and Ahmadzadeh, E. "Designing a realistic ICT closed loop SC network with integrated decisions under uncertain demand and lead time", *Knowledge-Based Systems*, **179**, pp. 34-54 (2019).

[10] Gholizadeh, H. Fazlollahtabar, H. and Khalilzadeh, M. “A robust fuzzy stochastic programming for sustainable procurement and logistics under hybrid uncertainty using big data”, *Journal of Cleaner Production*, **258**, pp. 120640 (2020).

[11] Ghaleb, M. Taghipour, S. Sharifi, M., et al. “Integrated production and maintenance scheduling for a single degrading machine with deterioration-based failures”, *Computers and Industrial Engineering*, **143**, pp. 106432 (2020a).

[12] Hendalianpour, A. “Optimal lot-size and price of perishable goods: a novel game-theoretic model using double interval grey numbers”, *Computers and Industrial Engineering*, **149**, pp. 106780 (2020).

[13] Ghaleb, M. Zolfagharinia, H. and Taghipour, S. “Real-time production scheduling in the Industry-4.0 context: Addressing uncertainties in job arrivals and machine breakdowns”, *Computers and Operations Research*, **123**, pp. 105031 (2020b).

[14] Liu, P. Hendalianpour, A. and Hamzehlou, M. “Pricing model of two-echelon SC for substitutable products based on double-interval grey-numbers”, *Journal of Intelligent and Fuzzy Systems*, **40**(5), pp. 8939-8961 (2021a).

[15] Sharifi, M. and Taghipour, S. “Optimal production and maintenance scheduling for a degrading multi-failure modes single-machine production environment”, *Applied Soft Computing*, **106**, pp. 107312 (2021).

[16] Liu, P. and Hendalianpour, A. “A branch and cut/metaheuristic optimization of financial SC based on input-output network flows: investigating the Iranian orthopedic footwear”, *Journal of Intelligent and Fuzzy Systems*, **41**(2), pp. 1-19 (2021).

[17] Liu, P. Hendalianpour, A. Razmi, J., et al. “A solution algorithm for integrated production-inventory-routing of perishable goods with transshipment and uncertain demand”, *Complex and Intelligent Systems*, **7**(3), pp. 1349-1365 (2021b).

[18] Ghaleb, M. Taghipour, S. and Zolfagharinia, H. “Real-time integrated production-scheduling and maintenance-planning in a flexible job shop with machine deterioration and condition-based maintenance”, *Journal of Manufacturing Systems*, **61**, pp. 423-449 (2021).

[19] Schroeder, M. and Lodemann, S. “A systematic investigation of the integration of machine learning into SC risk management”, *Logistics*, **5**(3), pp. 62 (2021).

[20] Nayal, K. Raut, R. D. Queiroz, M. M., et al. “Are artificial intelligence and machine learning suitable to tackle the COVID-19 impacts? An agriculture SC perspective”, *The International Journal of Logistics Management*, **34**(2), pp. 304-335 (2021).

[21] Akbari, M. and Do, T. N. A. “A systematic review of machine learning in logistics and SC management: current trends and future directions”, *Benchmarking: An International Journal*, **8**(10), pp. 2977-3005 (2021).

[22] Zhu, X. Ninh, A. Zhao, H., et al. “Demand forecasting with supply-chain information and machine learning: Evidence in the pharmaceutical industry”, *Production and Operations Management*, **30**(9), pp. 3231-3252 (2021).

[23] Hendalianpour, A. Fakhrabadi, M. Sangari, M. S., et al. “A combined benders decomposition and Lagrangian relaxation algorithm for optimizing a multi-product, multi-level omni-channel distribution system”, *Scientia Iranica*, **29**(1), pp. 355-371 (2022).

[24] Azimpoor, S. Taghipour, S. Farmanesh, B., et al. “Joint planning of production and inspection of parallel machines with two-phase of failure”, *Reliability Engineering and System Safety*, **217**, pp. 108097 (2022).

[25] Kosasih, E. E. and Brintrup, A. “A machine learning approach for predicting hidden links in SC with graph neural networks”, *International Journal of Production Research*, **60**(17), pp. 5380-5393 (2022).

[26] Arkat, J. Naseri, F. and Ahmadizar, F. “A stochastic model for the generalised cell formation problem considering machine reliability”, *International Journal of Computer Integrated Manufacturing*, **24**(12), pp. 1095-1102 (2011).

[27] Ghezavati, V. “A new stochastic mixed integer programming to design integrated cellular manufacturing system: A SC framework”, *International Journal of Industrial Engineering Computations*, **2**(3), pp. 563-574 (2011).

[28] Wang, J. Zhao, J. and Wang, X. “Optimum policy in hybrid manufacturing/remanufacturing system”, *Computers and Industrial Engineering*, **60**(3), pp. 411-419 (2011).

[29] Kim, E. Saghafian, S. and Van Oyen, M. P. “Joint control of production, remanufacturing, and disposal activities in a hybrid manufacturing–remanufacturing system”, *European Journal of Operational Research*, **231**(2), pp. 337-348 (2013).

[30] Sharifi, S. Chauhan, S. S. and Bhuiyan, N. “A dynamic programming approach to GA-based heuristic for multi-period CF problems”, *Journal of Manufacturing Systems*, **33**(3), pp. 366-375 (2014).

[31] Kia, R. Baboli, A. Javadian, N., et al. “Solving a group layout design model of a dynamic cellular manufacturing system with alternative process routings, lot splitting and flexible reconfiguration by simulated annealing”, *Computers and operations research*, **39**(11), pp. 2642-2658 (2012).

[32] Fattahi, P. Kheirkhah, A. S. and Esmailnezhad, B. “Stochastic cell formation problem within queuing theory and considering reliability”, *Advances in Industrial Engineering*, **50**(2), pp. 279-293 (2016).

[33] Wang, W. Wang, Y. Mo, D., et al. “Managing component reuse in remanufacturing under product diffusion dynamics”, *International Journal of Production Economics*, **183**, pp. 551-560 (2017).

[34] Liu, W. Ma, W. Hu, Y., et al. “Production planning for stochastic manufacturing/remanufacturing system with demand substitution using a hybrid ant colony system algorithm”, *Journal of Cleaner Production*, **213**, pp. 999-1010 (2019).

[35] Tayal, A. Solanki, A. and Singh, S. P. “Integrated frame work for identifying sustainable manufacturing layouts based on big data, machine learning, meta-heuristic and data envelopment analysis”, *Sustainable Cities and Society*, **62**, pp. 102383 (2020).

[36] Yang, K. Tong, L. and Xu, W. J. “Optimization of closed-loop SC with changes of external environment”, In *Proceedings of the Seventh International Forum on Decision Sciences. Uncertainty and Operations Research*, X. Li, and X. Xu, Eds., pp. 185-193, Springer, Singapore (2020).

[37] Liu, L. and Liu, S. “Integrated production and distribution problem of perishable products with a minimum total order weighted delivery time”, *Mathematics*, **8**(2), pp. 146 (2020).

[38] Szmelter-Jarosz, A. Ghahremani-Nahr, J. and Nozari, H. “A neutrosophic fuzzy optimisation model for optimal sustainable closed-loop SC network during COVID-19”, *Journal of Risk and Financial Management*, **14**(11), pp. 519 (2021).

[39] Fikry, I. Gheith, M. and Eltawil, A. “An integrated production-logistics-crop rotation planning model for sugar beet SCs”, *Computers and Industrial Engineering*, **157**, pp. 107300 (2021).

[40] Bank, M. Mazdeh, M. M. Heydari, M., et al. “Coordinating lot sizing and integrated production and distribution scheduling with batch delivery and holding cost”, *Kybernetes*, **51**(3), pp. 1151-1179 (2021).

[41] Nozari, H. Ghahremani-Nahr, J. and Szmelter-Jarosz, A. “A multi-stage stochastic inventory management model for transport companies including several different transport modes”, *International Journal of Management Science and Engineering Management*, **18**(2), pp. 1-11 (2022).

[42] Ghahremani-Nahr, J. Najafi, S. E. and Nozari, H. "A combined transportation model for the fruit and vegetable SC network", *Journal of Optimization in Industrial Engineering*, **15**(2), pp. 131-145 (2022a).

[43] Ghahremani Nahr, J. Mahmoodi, A. and Ghaderi, A. "Modeling the leader–follower SC network under uncertainty and solving by the HGALO algorithm", *Soft Computing*, **26**, pp. 13735–13764 (2022b).

[44] Torabi, S. A. and Hassini, E. "An interactive possibilistic programming approach for multiple objective SC master planning", *Fuzzy Sets and Systems*, **159**(2), pp. 193-214 (2008).

[45] Niakan, F. Baboli, A. Moyaux, T., et al. "A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment", *Journal of Manufacturing Systems*, **38**, pp. 46-62 (2016).

[46] Zaretalab, A. Hajipour, V. Sharifi, M., et al. "A knowledge-based archive multi-objective simulated annealing algorithm to optimize series–parallel system with choice of redundancy strategies", *Computers and Industrial Engineering*, **80**, pp. 33-44 (2015).

[47]Saidi-Mehrabad, M. and Safaei, N. "A new model of dynamic cell formation by a neural approach", *The International Journal of Advanced Manufacturing Technology*, **33**(9-10), pp. 1001-1009 (2007).

[48] Fang, C. Liu, X. Pardalos, P. M., et al. "A stochastic production planning problem in hybrid manufacturing and remanufacturing systems with resource capacity planning", *Journal of Global Optimization*, **68**(4), pp. 851-878 (2017).

[49] Egilmez, G. Erenay, B. and Süer, G. A. "Stochastic skill-based manpower allocation in a cellular manufacturing system", *Journal of Manufacturing Systems*, **33**(4), pp. 578-588 (2014).

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Mohammad Fallah is a professor of Industrial Engineering at Islamic Azad University-Central Tehran Branch in Iran. He received his PhD degree at Azad University Science and Research Branch in Iran. His research interests include supply chain management, mathematical modeling, and the use of heuristic and meta-heuristic methods in optimizing systems design, closed-loop supply chain, strategic management, process redesign, business management Project, and Game theory.

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Table 1

Author	Model features	Solution approach	Uncertain parameters
Arkat [26]	configuration costs minimization	Lingo	Time of breakdown or failure
Ghezavati et al. [27]	Inventory costs and production planning	GA-SA	Demand and processing time
Wang et al. [28]	Combined Reproduction-Reproduction Systems for Products with a Short Life Cycle, Potential Demand and Number of Products Returned and Total System Costs	Simplex	Time of breakdown or failure
Kim et al. [29]	Investigating the effect of decision integration in a combined reproduction-production system	Wagner with initiative	–
Sharifi et al. [30]	costs minimization	GA, Lingo	–
Kia et al. [31]	costs minimization	GA	–
Fattahi et al. [32]	Maximize the average waiting time	Lingo + Genetics	Processing time and demand entry time
Wang et al. [33]	Create a simulation of the introduction of a new product into target markets.	Simplex	–
Liu et al. [34]	Design of a combined reproduction-production system with respect to resource reduction and environmental degradation	ACO	–
Diabetes et al. [8]	Its goal is to cut down on the time and expense involved in getting items to consumers.	Lagrange and epsilon-constraint	–
Vahdani et al.	To increase overall profit, provide a closed-loop SC network that accounts for erratic demand and the	GA	Demand and

[9]	amount of time it takes to complete an order.		shipping time
Tayal et al. [35]	Two-objective problem in order to maximize performance and minimize operating costs	GA	–
Yang et al. [36]	Provide a closed-loop SC by reproducing in a Stockholm game framework and considering the effects of green design on consumers	Simplex	–
Gholizadeh et al. [10]	Create a model with many objectives, such as reducing overall expenses, improving the effectiveness of transportation, and reducing information fraud in the information-sharing process.	heuristic	–
Liu and Liu [37]	To gauge the degree of customer service, provide a manufacturing and distribution challenge for perishable goods that aims to reduce the overall order-weighted delivery time.	heuristic	-
Szmelter-Jarosz et al. [38]	Constructing a closed-loop SC network is an effective strategy for dealing with uncertainty.	Neutrosophic fuzzy	Demand-Transportation Cost
Fikry et al. [39]	Describe a tactical and strategic methodology for reducing SC costs for sugar beets.	Cplex	-
Bank et al. [40]	Describe a technique for achieving the best possible balance between the sequence-dependent setup costs, holding costs, delivery costs, and penalty costs in a production-distribution system that includes lot size considerations.	GA	-
Nozari et al. [41]	Create a stochastic inventory model with a variety of transport modalities for the benefit of transportation businesses.	GA-PSO-GWO	Demand-Transportation Cost
Ghahremani-Nahr et al. [42]	Develop a networked transportation mechanism to provide fresh produce.	GA – SCA	Demand-Transportation Cost
Ghahremani-Nahr et al. [43]	Create an unpredictable leader-follower SC network model that aims to maximize profit	HGALO	Demand-Transportation Cost
Niakan et al. [45]	configuration costs + social metrics minimization	NSGAII + SA	–
Saeedi Mehrabad et al. [47]	Inventory costs and production planning minimization	Lingo	–
Fang et al. [48]	Reduce system expenses based on demand.	Lagrange	Demand
Egilmez et al. [49]	Maximize production rates	Arena simulation software	Demand and processing time
current paper	designing a dual-objective green model for an integrated manufacturing system that both reduces the system's prospective costs and greenhouse gas emissions	MOGWO and NSGA II	Demand - Operating costs - Processing time

Table 2

Parameter	*Random*	*Parameter*	*Random*	*Parameter*	*Random*

	boundaries		boundaries		boundaries
$\tilde{D}_i^s$	$\sim U\left[50,120\right]$	B_{ji}	$\sim U\left[1,2\right]$	μ_m	$\sim U\left[30,40\right]$
$\tilde{E}_i$	$\sim U\left[1,5\right]$	$\varnothing_j$	$\sim U\left[100,500\right]$	L_c	2
$\tilde{W}_i$	$\sim U\left[1,5\right]$	k_j	$\sim U\left[100,500\right]$	U_c	10
$\tilde{T}_{im}$	$\sim U\left[2,10\right]$	τ_j	$\sim U\left[100,500\right]$	ξ_i	0.3
σ_m	$\sim U\left[5,10\right]$	χ_j	$\sim U\left[7,9\right]$	γ_{im}	$\sim U\left[0,1\right]$
ε_m	$\sim U\left[30,60\right]$	$MTBF_m$	$\sim U\left[20,30\right]$	O_i^s	$\sim U\left[2800,3000\right]$
β_m	$\sim U\left[1,2\right]$	$MTTR_m$	$\sim U\left[10,20\right]$	Co_{imc}	$\sim U\left[150,200\right]$
G_{mc}	$\sim U[100,190$	Q_m	$\sim U\left[120,230\right]$	C_j	$\sim U\left[120,180\right]$

Table 3

Efficient solution	*OBFV1*	*OBFV2*
OBF1	*482671.51*	-
OBF2	-	*1144*
1	*486463.11*	*1977*
2	*487104.80*	*1868*
3	*488364.20*	*1766*
4	*489177.47*	*1673*
5	*493203.22*	*1481*
6	*494485.39*	*1395*
7	*496220.86*	*1315*
8	*497786.88*	*1268*
9	*498700.64*	*1237*
10	*499162.60*	*1213*
11	*499473.33*	*1211*
Average efficient solutions	*493649.31*	*1491.27*

Table 4

		Cell						
		1	2	3	4	5	The total number of machines	Rate of use
Machine	*5*	-	-	2	2	-	4	0.986
Machine	*6*	2	2	-	-	2	6	0.942

Table 5

Parts	*Machines*	*Cell*					*Production rate in scenario 1*	*Production rate in scenario 2*
		1	*2*	*3*	*4*	*5*		
1	*5*	-	-	*1*	-	-	*50*	*34*
2	*6*	*1*	*1*	-	-	*1*	*24*	*26*
1	*5*	-	-	-	*1*	-	*32*	*46*
2	*6*	*1*	*1*	-	-	-	*45*	*72*

Table 6

α_1	α_2	*OBFV1*	*OBFV2*	α_1	α_2	*OBFV1*	*OBFV2*
0.1	*0.9*	*484133.48*	*1345.48*	*0.1*	*0.1*	*484436.18*	*1348.67*
0.2	*0.8*	*488644.25*	*1382.34*	*0.2*	*0.2*	*489533.84*	*1397.25*
0.3	*0.7*	*490345.64*	*1435.67*	*0.3*	*0.3*	*491348.67*	*1451.37*
0.4	*0.6*	*492014.67*	*1480.67*	*0.4*	*0.4*	*493649.31*	*1491.27*
0.5	*0.5*	*493034.81*	*1534.28*	*0.5*	*0.5*	*493947.25*	*1564.17*
0.6	*0.4*	*493566.74*	*1597.67*	*0.6*	*0.6*	*494277.64*	*1623.55*
0.7	*0.3*	*494021.74*	*1653.27*	*0.7*	*0.7*	*494566.72*	*1690.47*
0.8	*0.2*	*494866.66*	*1707.51*	*0.8*	*0.8*	*495023.17*	*1737.48*
0.9	*0.1*	*495372.19*	*1755.67*	*0.9*	*0.9*	*496233.20*	*1787.20*

Table 7

ξ_i	*OBFV1*	*OBFV2*
0.1	*494237.28*	*1524.67*
0.2	*493955.27*	*1510.34*
0.3	*493649.31*	*1491.27*
0.4	*493117.64*	*1484.20*
0.5	*492673.24*	*1467.90*
0.6	*492010.99*	*1428.46*

0.7	*491137.48*	*1406.24*
0.8	*490837.48*	*1384.25*
0.9	*488744.18*	*1334.42*

Table 8

Algorithm	*Problem*	*OBF1*	*OBF2*	*NPF*	*MSI*	*SM*	*MID*	*Cpu time*
NSGA II	*1*	*590358.06*	*1691.24*	*15*	*25787.94*	*30191.61*	*0.630*	*18.230*
	2	*653455.69*	*3128.34*	*17*	*39884.08*	*28961.60*	*0.880*	*54.000*
	3	*777028.41*	*4068.37*	*25*	*35945.16*	*46713.31*	*0.590*	*85.150*
	4	*813523.81*	*6353.92*	*12*	*30651.97*	*53775.69*	*0.640*	*121.265*
	5	*909600.71*	*7356.04*	*23*	*31256.82*	*33778.50*	*0.550*	*167.750*
	6	*968866.15*	*7529.48*	*20*	*39801.00*	*51220.79*	*0.790*	*217.200*
	7	*1058001.38*	*8247.03*	*16*	*28298.03*	*47013.28*	*0.840*	*272.885*
	8	*1165602.41*	*8759.13*	*13*	*45948.33*	*20268.61*	*0.770*	*334.535*
	9	*1274458.26*	*10931.71*	*16*	*41482.35*	*44086.82*	*0.710*	*409.800*
	10	*1371152.19*	*13302.91*	*17*	*49358.23*	*35470.85*	*0.820*	*479.835*
	11	*1430621.18*	*15768.67*	*11*	*49496.07*	*56639.65*	*0.820*	*520.065*
	12	*1540516.25*	*15852.55*	*19*	*47348.58*	*20046.04*	*0.840*	*662.970*

	13	1707951.17	17680.22	13	26176.13	38497.97	0.820	763.680
	14	1797490.74	20173.02	16	27408.21	36973.96	0.970	905.180
	15	1840703.86	24889.38	19	36185.99	38436.65	0.600	1338.16
MOGWO	1	592201.84	1701.29	14	48271.61	43104.79	0.850	11.230
	2	654723.80	3052.38	14	51361.14	29674.15	0.620	12.990
	3	780171.16	3818.02	19	45190.48	43542.18	0.560	16.880
	4	815673.04	6321.92	14	55499.53	34140.71	0.800	31.453
	5	903292.89	7293.08	23	52958.97	21072.88	0.730	43.453
	6	967509.08	7299.57	25	59216.23	25276.23	0.730	91.880
	7	1021499.57	8120.22	21	48283.35	41652.74	0.830	118.713
	8	1156451.12	8650.68	15	43128.64	34204.58	0.890	165.120
	9	1280689.90	11180.00	19	37640.73	24581.64	0.680	241.440
	10	1326601.17	13188.60	11	50273.97	30233.74	0.830	325.880
	11	1473669.76	15277.51	24	54470.06	38221.68	0.710	442.660
	12	1524203.68	15468.23	24	45586.32	25752.36	0.920	618.787
	13	1729097.74	18069.18	23	37270.58	42152.81	0.920	774.563
	14	1800951.02	20224.35	14	41661.79	27285.49	0.630	993.453
	15	1824006.38	23292.50	19	38841.42	47522.73	0.810	1334.45

Table 9

Indicator	*Algorithm*	*Average*	*Standard deviation*	*95% confidence interval*	*T-value*	*P-value*
MOBV1	*NSGA II*	*1190049*	*106862*	*(-306472 312950)*	*0.02*	*0.983*
	MOGWO	*1193289*	*139023*			
MOBV2	*NSGA II*	*11049*	*1731*	*(-5136 4766)*	*0.08*	*0.939*
	MOGWO	*10864*	*1681*			
NPF	*NSGA II*	*16.80*	*1.0*	*(-5.02 1.42)*	*1.15*	*0.261*
	MOGWO	*18.60*	*1.2*			
MSI	*NSGA II*	*37002*	*2202*	*(-16087 4529)*	*1.24*	*0.197*
	MOGWO	*47310*	*1748*			
MID	*NSGA II*	*38805*	*2896*	*(-2526 12347)*	*1.36*	*0.186*
	MOGWO	*33895*	*2157*			
SM	*NSGA II*	*0.751*	*0.032*	*(-0.1045 0.0725)*	*0.37*	*0.714*
	MOGWO	*0.767*	*0.029*			
CPU Time	*NSGA II*	*423*	*95*	*(-217 367)*	*0.53*	*0.601*

```
Input the main parameters of MOGWO
    for i=1:number of grey wolves
        Create a randomly generated solution
        Calculate the objective functions value
    end for
    sort the solutions based on the objective function values
        Alpha   the best solution
        Beta    the second best solution
        Delta   the third best solution
    it=1;
        while it < maximum number of iterations
            for i=1: npop
                update the position of wolves
                Calculate the fitness
            end for
            Decrease the search radius
            Update A and C
            Update the Alpha, Beta and Delta
    it=it+1;
      end while
```

Figure 1

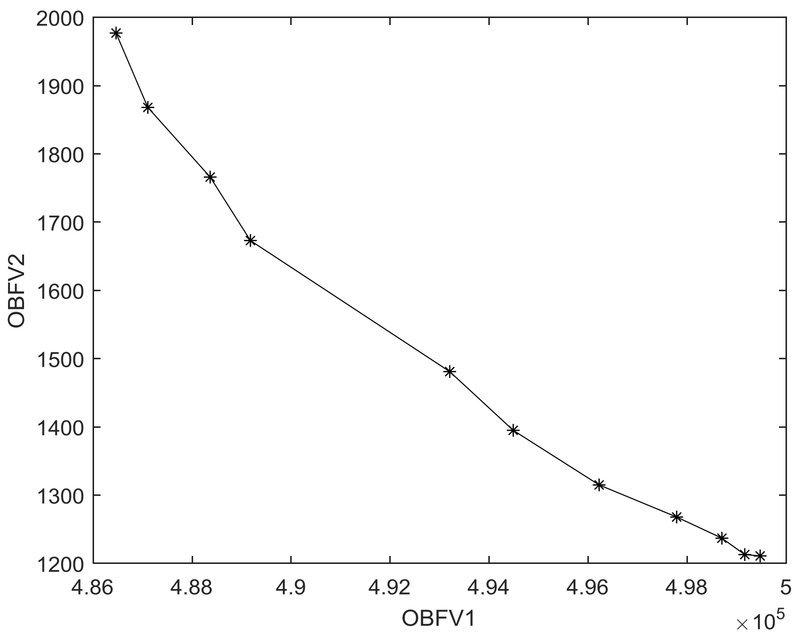

Figure 2

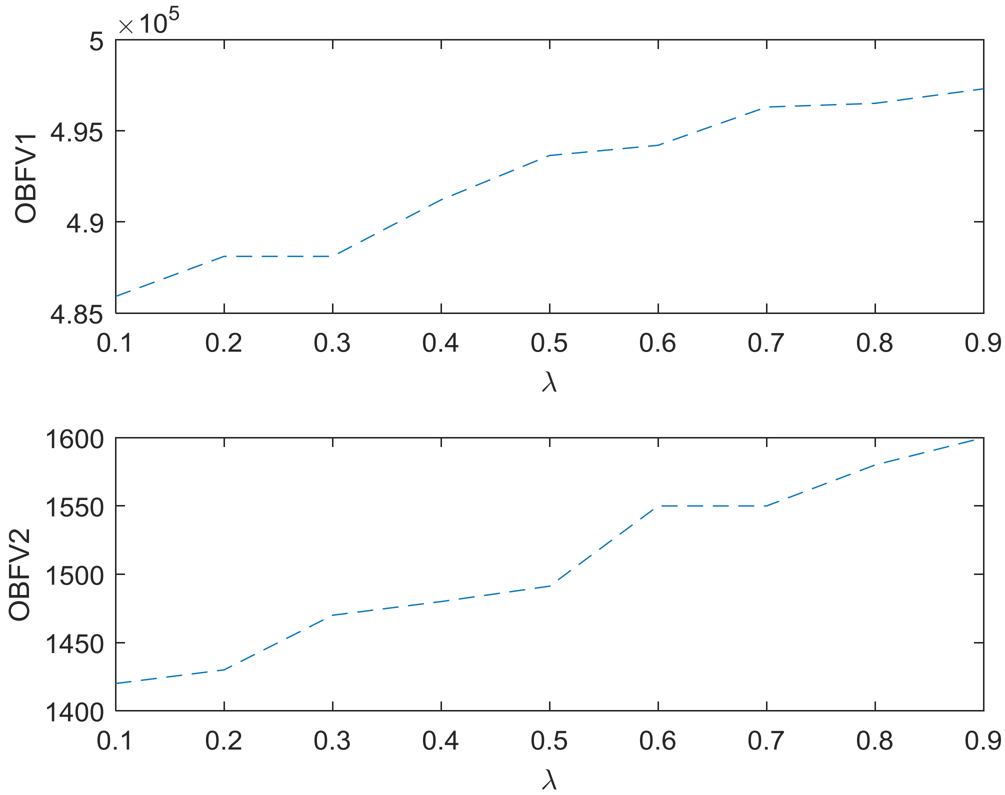

Figure 3

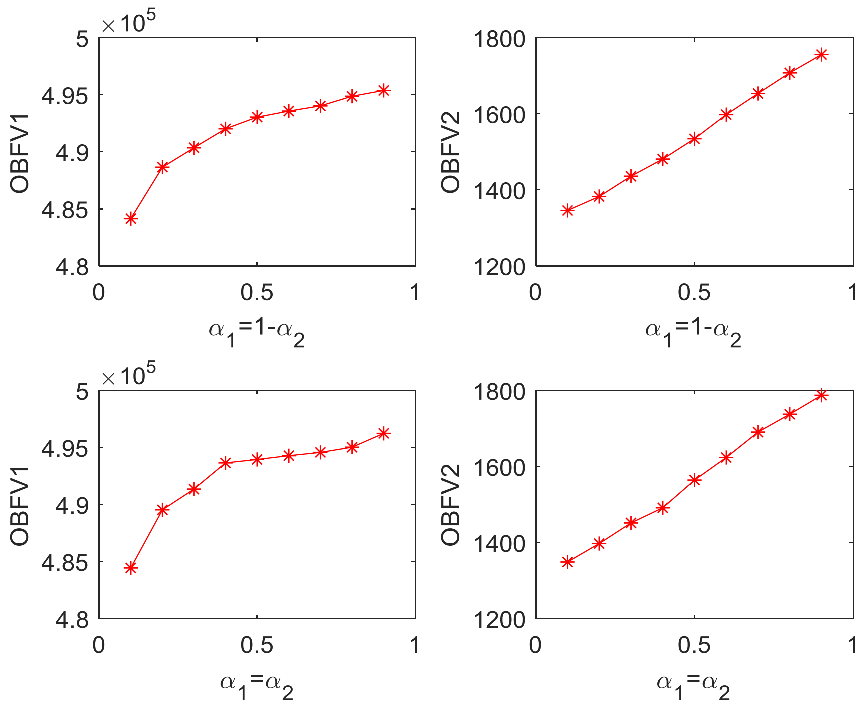

Figure 4

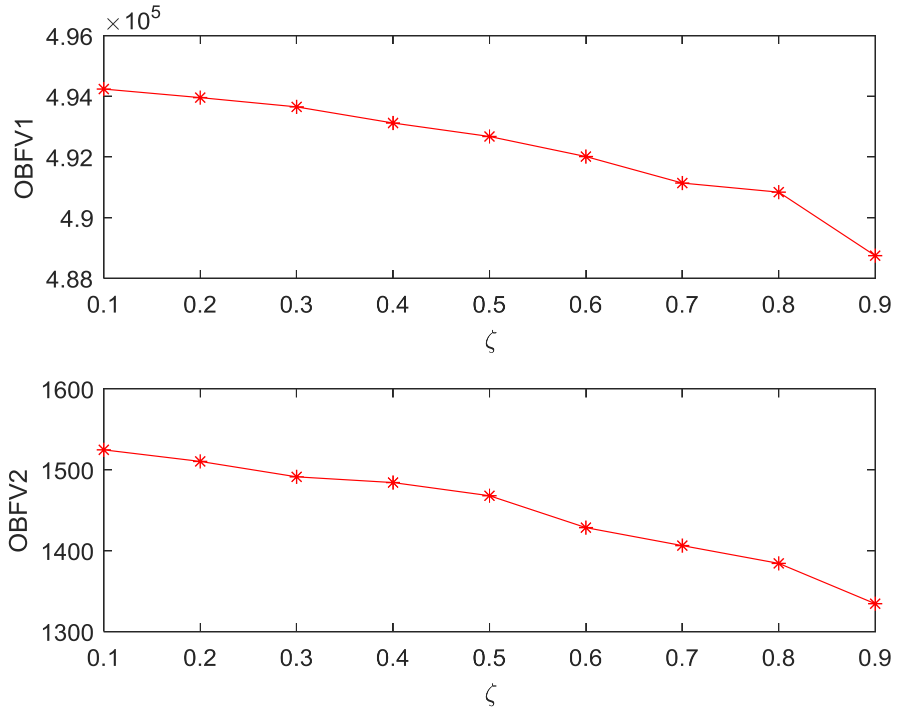

Figure 5

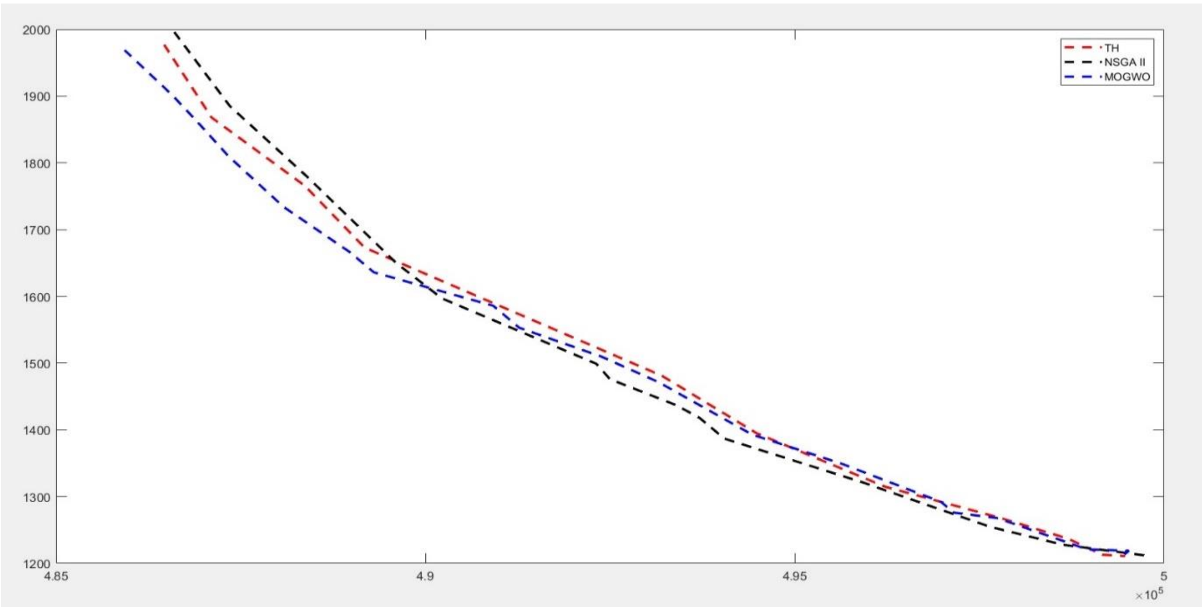

Figure 6

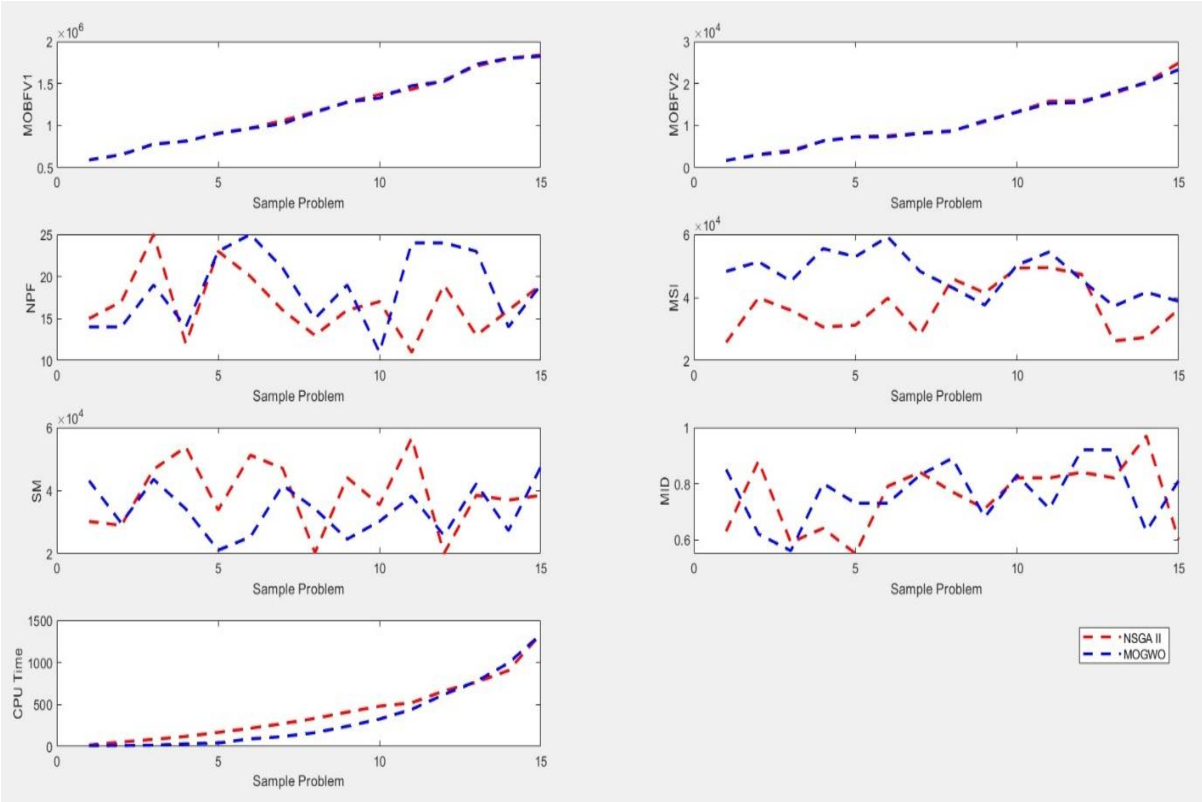
MOBFV1
Sample Problem
MOBFV2
Sample Problem
NPF
Sample Problem
MSI
Sample Problem
SM
Sample Problem
MID
Sample Problem
CPU Time
Sample Problem
NSGA II
MOGWO

Figure 7