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A Multi-Objective Mathematical Model for Dynamic Cellular Manufacturing System Design under Uncertainty: A Sustainable approach

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Abstract *– Using a case study in scaffold production, this paper aimed to develop an integrated multi-objective mathematical model for a dynamic and sustainable cellular manufacturing system under fuzzy uncertainty. In this field, most studies have considered only the economic component or at most two components of sustainable production. Furthermore, with increasing concerns about global warming, environmental issues have become particularly important in manufacturing products and goods. On the other hand, customer satisfaction as one of the social responsibility cases is crucial because customer satisfaction is one of the factors of sustainability of organizations and companies in a competitive environment. Accordingly, sustainable production in this article consists of three components: economic, environmental, and social responsibility. We also subjected sustainable production in a dynamic cellular manufacturing system to fuzzy uncertainty. A sustainable multi-objective mathematical model with objective functions of minimizing costs, minimizing CO2 emissions, and minimizing product shortages (customer satisfaction) was proposed. A case study on scaffolding production was solved in GAMS software with CPLEX solver and augmented Epsilon-constraint method, and its basic variables were investigated to validate the proposed model. Then, due to the high complexity of the cellular manufacturing model, the NSGA-II and MOPSO meta-heuristic algorithms were applied to solve larger problems. As the results can be shown, the NSGA-II algorithm performed better than the MOPSO algorithm. Therefore, the results are then analyzed on the NSGA-II approach. The results indicate the proper performance of the proposed solution approach*

Keywords*– Dynamic cellular manufacturing systems, Sustainable production, NSGA-II, Advances epsilon-constraint, Taguchi method*

INTRODUCTION

The last century has been a century of rapid advancement in manufacturing technology. To adapt to the global competitive markets progress, which is characterized by the specialization of needs, shortening the products' life cycle, shortening the supply of products in the market, and the customers' various demands, manufacturing units must take measures that increase the fruitfulness of production activities and processes related (Khalilzadeh et al., 2021). Manufacturers ought to modify their production systems to manufacture their products at low cost, high quality, and in the fastest possible time for timely delivery to customers. These systems must also adapt quickly to changes in demand

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and product design without the need to spend money on rearranging (Moldavska & Anastasiia, 2016). In this regard, dynamic cellular manufacturing is one of the newest production concepts that has been considered in recent decades. The benefits of implementing this system are increasing the efficiency and productivity of labor and space, reducing costs, reducing inventory under construction, and improving production programming. It should be noted that the manufacturing enterprises' owners have recently considered sustainable production, and the benefits of its implementation include improving the employees' morale and health level, their responsibility and environmental protection, reducing pollution, and increasing profitability (Mungwattana & Anan, 2000; Rheault et al., 1995; Babaeinesami & Ghasemi, 2021).

Cellular manufacturing is derivative of principles of group technology, which were proposed by Flanders in 1925 and adopted in Russia by Mitrofanov in 1933 (Brandon & John, 1996). Burbidge actively promoted group technology in the 1970s. "Apparently, Japanese firms began implementing cellular manufacturing sometime in the 1970s," and in the 1980s cells migrated to the United States as an element of just-in-time (JIT) production (Duffner et al., 2021). For implementing dynamic cell manufacturing, first, the parts to be made must be grouped by into families. Then a systematic analysis of each family must be performed; typically in the form of production flow analysis (PFA) for manufacturing families, or in the examination of design/product data for design families. This analysis can be time-consuming and costly but is important because a cell needs to be created for each family of parts. Cellular manufacturing brings scattered processes together to form short, focused paths in concentrated physical space. So constructed, by logic a cell reduces flow time, flow distance, floor space, inventory, handling, scheduling transactions, and scrap and rework (Forghani et al., 2021). Moreover, cells lead to simplified, higher validity costing, since the costs of producing items are contained within the cell rather than scattered in the distance and the passage of reporting time (Fesnak, 2020).

A large and growing number of manufacturers are realizing substantial financial and environmental benefits from sustainable business practices. Sustainable production is the creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources. Sustainable production also enhances employee, community and product safety. There are a number of reasons why companies are pursuing sustainable production (Espro et al., 2021):

- Increasing operational efficiency by reducing costs and waste
- Response to or reaching new customers and increase competitive advantage
- Protecting and strengthening brand and reputation and building public trust
- Building long-term business viability and success
- Response to regulatory constraints and opportunities

Given the importance of these two issues, methods should be proposed to integrate them to expand the literature. In this regard, cellular manufacturing systems are among the new production methods that are used today in most large production centers with relatively high product diversity and multi-purpose facilities (Defersha & Chen, 2008; Shafipour-omran et al., 2020). The concept of sustainable production emerged at the 1992 United Nations Conference on Environment and Development; and it is very closely related to the concept of sustainable development. The main reason for the disappearance of the environment is the unstable pattern of production and consumption, especially in industrialized countries. While sustainable consumption targets consumers, sustainable production is associated with companies and organizations that produce products or provide services (Mishra et al., 2020; Shafipour-Omrani et al., 2021). The advantages of using this system in the production of products include reducing the inventory of semi-finished products, reducing the start-up time of machines, reducing waste and reworking. The supply chain in the production network seeks to create coordination between production facilities, suppliers, and product allocation to product markets (Drolet et al., 2008). Most manufacturing companies first design the supply chain, the number, and locations of production facilities and decide which product markets each facility serves. Then they organize the processes (production line, cell arrangement, etc.) in each facility. In this case, the cellular arrangement will be made without considering the production network and chain. In recent years, the industry section used cellular manufacturing system advantages, and a new production method, including lessening the transportation amount and cost, lead time, production time, package size, inventory in the manufacturing process, etc. Today, manufacturing factories owing to being in the global competitive markets movement, characterized by the needs' specialization, shortening the product life cycle and product supply cycle to the market, and the various demands of customers, must conform to these conditions and take measures to improve the competence of production processes; thus, a co-production system called dynamic cellular manufacturing was developed (Bajestani et al., 2009). Also, industry 4.0 conceptualizes rapid change to technology, industries and societal patterns and processes in the 21st century due to increasing interconnectivity and smart automation. Industry 4.0 has many challenges in field's environmental issues and social issues (for example its benefits should be shared fairly, its benefits should be human command and human-oriented, management external factors). By research in the fields of integrating industry 4.0 and sustainable manufacturing this problem can be solved (Machado et al., 2020).

It should be noted that no article was found that simultaneously examines dynamic manufacturing with all sustainability criteria, so the literature gap is noticeable. So we have to enter this field and consider a mathematical model for a dynamic and sustainable cellular manufacturing (Ghasemi et al., 2021). In this regard, Tavakkoli-Moghaddam et al. (2008), assume an extended model in which components in packets are moved between cells with assumptions such as alternative operations plan, sequence of operations, machine capacity, and the ability to reproduce machines. Their model's purpose was to minimize the sum of the machines' fixed and variable costs, intercellular displacement, and reconfiguration. (Tavakkoli-Moghaddam et al., 2009) also described implementing an imitation algorithm for dynamic reconfiguration in CM with an alternative operation scheme. (Drolet et al., 2008), proposed a fuzzy genetic algorithm for the bi-objective cell arrangement problem in a dynamic environment that considers both present and absent strategies in the problem. The machines are fixed along the entire planning horizon in the absentee strategy, but a different combination of machines is allowed in each planning period in the current strategy. (Saidi-Mehrabad & Safaei, 2007), presented a comprehensive mathematical model with dynamic cell configuration, alternative routing, component distribution, operation sequence, multiple units of identical machines, machine capacity, workload balance between cells, operating cost, subcontracting cost, the consumables' cost, preparation cost, the size of the cell, and the proximity of the machines. (Safaei et al., 2008), proposed an innovative two-phase genetic algorithm to solve a comprehensive mathematical model with characteristics similar to previous work. (Safaei et al., 2008; Saidi-Mehrabad & Safaei, 2007), developed a comprehensive mathematical model for dynamic production cell arrangement for multiple items, the context of stacked volume at multiple levels, and the effect of stacked volume on product quality. There are more practical and integrated factors in it that make it more complex but closer to reality. Sustainable production is through economic processes that minimize negative environmental impacts while saving energy and natural resources and increasing employee satisfaction, community safety, and product health. Sustainable production has economic, social, and environmental dimensions. As we know, sustainable production has social, economic, and environmental aspects. The introduction of these concepts in industry and production will increase the efficiency and prosperity of production and respect for human issues in terms of psychological and physical issues, respect for the environment in all aspects, and further progress in economic concepts. For example, in this article, an example of safe scaffolding production is given, which we do not benefit from the lack of this knowledge in the whole world, which is the manifestation of three criteria of sustainable production. Every year, many workers lose their lives or become disabled due to non-compliance with safety issues. The urban environment is ugly because of old and unsafe scaffolding, and more iron is used to erect old scaffolding. This example alone illustrates the need for research in this area. On the other hand, the benefits of cellular manufacturing mentioned earlier, the integrated consideration of dynamic and sustainable production, multiplies the issue's importance. Given the above, the body of literature about sustainable production is the thing, so it is necessary to use a sustainable method in this area to enrich the literature.

Azadeh et al. (2017) stated that sustainable production combines a triple bottom line approach (financial, environmental, and social) of production methods. Decision-making in such a complex system becomes challenging in terms of selecting and prioritizing various aspects. Their research prioritizes sustainable production barriers by calculating weight by using the best method-worst method in an Indian manufacturing organization. For prioritization, the final intensity (weight) of 39 barriers was calculated using the best method-worst method. The findings of this study considered financial and managerial barriers as the most important ones among the main barriers to sustainable production, followed by organizational barriers, social and environmental barriers, technological barriers, knowledge and learning barriers, and independent barriers. (Beekaroo et al., 2019) reviewed sustainability indicators of Morituri manufacturing companies, which examined these indicators in 30 Morituri manufacturing companies in terms of 9 environmental indicators, four financial indicators, and two social indicators. (Zhao & Wu, 2000) in their research, inspected quality management in sustainable production. They changed their focus from the number of defects to their intensity, as the authors believed that the intensity of defects has different effects on the sustainability indicators. (Zheng et al., 2020) focused on saving energy and reducing pollution by reducing production deficits. In contrast, previous research has focused on reducing time and labor. Shafiee-Gol et al. (2021) presented a mathematical model to design dynamic cellular manufacturing systems in multiple plants. The production planning and location–allocation decisions are the valuable outputs of their research. Maximizing sale revenue and minimizing total costs of machine operating, machine overhead, inter-cell material handling, inventory holding, and outsourcing cost are the objectives in their research. The two meta-heuristics algorithms as grey wolf optimization and genetic algorithm are customized to solve their problem. Sadeghi et al. (2021) stated that integrating cellular manufacturing into supply chain affected service level. The simulation based on OptQuest evaluated inventory parameters estimated in the design phase is the main novelty of their paper. The statistical analysis result indicates that Re-Order Point (ROP) values changed compared with ROP values estimated in the design phase.

Table I. Literature review

Author	*Cell manufacturing*		*Solution procedure*			*Type of model*						*Number of Objectives*		*Objective Function*					*Period*		*Echelon Number*	
	Dynamic	*Static*	*Exact*	*Heuristic*	*Meta Heuristic*	*Nonlinear*	*Fuzzy*	*Scenario Base*	*Stochastic*	*Probabilistic*	*Linear*	*Single*	*Multi*	*Social OBJ*	*Cost*	*Environmental*	*Distance*	*time*	*Single*	*Multi*	*Single*	*Multi*
Azadeh et al. (2017)			•						•			•		•	•	•			•			•
Shafiee-Gol et al. (2021)		•	•				•					•			•			•		•		•
Sadeghi et al. (2021)			•				•						•		•	•				•		•
Moradi et al. (2021)		•	•								•	•			•			•		•		•
Pagone et al. (2020)		•			•			•	•									•	•		•	
Zheng et al. (2020)		•	•					•	•				•		•					•		•
Beekaroo et al. (2019)			•						•				•		•					•		•
Klibi et al. (2013)		•	•						•		•	•		•	•				•			•

Saidi et al. (2007)		•		•							•	•			•				•			•
This Research	•		•		•		•						•	•	•	•				•		•

Moradi et al. (2021) presented a robust optimization approach for designing a multi-echelon, multi-product, multi-period supply chain network with outsourcing. The demands of retailers, production capacities, and transportation costs as well as costs of opening distribution centers were subject to uncertainty. A set of numerical experiments using nominal and realisation data was investigated and the relative performance of the robust and deterministic models was compared based on the standard deviation. Pagone et al. (2020) discuss the concept of decision-making in the components' selection according to sustainability criteria, in which 18 criteria are divided into 4 groups of time, cost, quality, and environment, and through TOPSIS, they concluded that aluminum alloy would be the best choice for producing car parts. Furthermore, in real terms, the nature of many production parameters such as product demand, available machine capacity, and production time is uncertain. Therefore, it is difficult to determine the cellular arrangement, the amount of production, and the purchase amount according to the demand for customers' products in a competitive market that faces uncertainty. Also, the dynamic and complex nature of the supply chain imposes many uncertainties on the supply chain. In this way, it severely affects the overall performance of the supply chain (Klibi et al., 2013). To this end, (Ho, 1989) divides uncertainties that affect real phenomena into two groups: (1) environmental uncertainty; and (2) systemic uncertainty. Regarding the supply chain concept, environmental uncertainty is related to uncertainty in supply and demand, which depends on the performance of suppliers and customer behavior. System uncertainty is associated with uncertainty in production, distribution, collection, and recycling. This type of uncertainty can include uncertainty at the time of delivery, production costs, and various processes' actual capacity. We also know that the strategic horizon of supply chain network design dramatically increases the intensity of the uncertainties' effect. In addition, according to (Liu & Iwamura, 1998), uncertainty can be seen as both stochastic and probabilistic. Experiments can find the distribution function, and probabilistic programming approaches are used to deal with uncertainty. Possibility theory is used to evaluate mental analysis, where we are faced with some unknown parameters. The model has imprecise parameters when the probabilistic distribution is used. All of this leads us to use fuzzy theory to deal with uncertainty. Given the above discussion, the motivation for this paper is to consider an integrated multi-objective mathematical model for a dynamic and sustainable cellular manufacturing system under uncertain conditions. In summary, the innovations that distinguish this research from other research and can enrich the literature in this field are as follows: integrating dynamic cellular manufacturing systems with sustainable production concepts (financial, environmental, and social responsibility) in the face of uncertainty.

In this regard, we will try to present multi-objective mathematical models for group layout design in 1- Dynamic cell formation to reduce the corresponding cost, and secondly, the reduction in cost and time related to the concepts of sustainable production in a dynamic cellular manufacturing system and increasing real-world system efficiency in safe scaffolding production. In this regard, we will try to use a meta-heuristic approach to solve the proposed models. This research could be used in the future by researchers and students studying dynamic cellular manufacturing systems. One of the innovations of this research goes back to the fact that in addition to the typical research that is generally done in the field of dynamic cellular manufacturing systems, in this article, sustainable production is also integrated with this issue and three dimensions of sustainability. (Economic, environmental and social responsibility) has also been used in this issue. Also, due to the uncertainty conditions (fuzzy data), the production environment is considered more realistic, and also Nayr's meta-heuristic method is used to solve the proposed problem. In addition, the implementation of this issue in the safe scaffolding industry is another highlight of this research. Having a unified view of the above points is an issue that is very important for the reasons mentioned. This is one of the research gaps (especially in the real world and especially in scaffolding production). In other words, no research has been conducted simultaneously considering the three dimensions of sustainable production. This article is planned as follows. In the next chapter, the method of use in the structure of the article is described. In Chapter 3, the mathematical model is developed. In Chapter 4, the model of possible linear programming model is used. In Chapter 5, a case study is used to validate the model. In Chapter 6, the multi-objective genetic meta-heuristic algorithm is used to solve the model. In Chapter 7, statistical analysis of parameter adjustment is performed by the Taguchi method. Finally, in Chapter 8, the article concludes and provides directions for future research.

II. THE METHOD USED IN THE ARTICLE STRUCTURE

Here, due to research gaps mentioned earlier, the position of this research was determined, followed by the definition of the problem and research assumptions such that it can cover the shortcomings of the study area as much as possible. First, the fuzzy mathematical model is presented, and then the Defuzzification method is explained, and its model is presented. Finally, a small-sized example is solved in GAMS software with a CPLEX solver and with a partial constraint method to validate the proposed model, and the results are expressed.

III. PROBLEM STATEMENT

Cellular manufacturing systems are among the new methods used today in most large production centers with relatively high product diversity and multi-purpose facilities (Tavanayi et al., 2021). The basis of a cellular manufacturing system is the classification of products and machines based on their physical, operational, or processing similarity into several smaller production units called cells. Cells can be physical or virtual. On the other hand, in most production units, the traditional perspective is used for supply and distribution planning. That is, each of these components independently plans for its activities.

In recent years, the industry has benefited from cellular manufacturing system privileges, which is one of the new production methods, including reducing the amount and cost of transportation, lead time, production time, package size, inventory in the manufacturing process, etc. Today, manufacturing factories must adapt to these conditions and improve the efficiency and productivity of production processes. The need for companies to adopt themselves is due to being in the global competitive markets movement, which is characterized by the specialization of needs, shortening the product life cycle, shortening the product supply cycle to the market, and the various demands of customers; hence a co-production system called dynamic cellular manufacturing was developed.

Sustainable production has economic, social, and environmental dimensions. Sustainable production is the creation of goods produced through economic processes that minimize negative environmental impacts while saving energy and natural resources and increasing employee satisfaction, community safety, and product health.

A. Mathematical model

Assumptions:

The problem’s assumptions are as follows:

1- Shortage is allowed and limited.

2- Each machine has a fixed cost as an overhead cost which is not related to its consumption.

3- The variable cost of each machine depends on its working hours.

4- If a machine is purchased, it must be in the workshop in the next period, and its removal is not considered.

5- Partitioning between cells is not considered, and one place can be assigned to different cells.

6- Moving machines include installing and removing. When a machine is moved from one place to another, both installation and removal costs are charged. Also, regardless of the cost of purchasing a machine, the installation cost is considered for them.

7- Intracellular and extracellular transfer costs of products are linear functions of distance.

8- For the number of machines dedicated to each cell, an upper and lower frontiers are considered. A large number of machines in each cell complicates the production control in them. On the other hand, the very small number of machines in the cell increases the costs of intercellular transfer.

9- The shape and position of the cells are not predetermined.

10 - Operators based on their expertise can operate on the machines in question, and there is no constraint to the number of operators.

In this section, the desired fuzzy mathematical model is presented. The proposed mathematical model has three objective functions. In the following, the constraints, objective functions, and a brief description of them are provided.

Sets and numerators

p	Products type set $p \in \{1,2,\dots,P\}$
h	Periods set $h \in \{1,2,\dots,H\}$
r	Set of required operation to be done on product $r \in \{1,2,\dots,R_p\}$
c, c'	Cells set $c \in \{1,2,\dots,C\}$
l, l'	Set of machines deployment locations $l \in \{1,2,2\dots,L\}$
w, w'	Set of operators based on their specialty $w \in \{1,2,\dots,W\}$
Parameters	
$\tilde{I}_p$	Intracellular transfer cost per unit of product p per unit distance
$\tilde{E}_p$	Intercellular transfer cost per unit of product p per unit distance
$\tilde{d}_{ph}$	Demand for product “p” at time “h”
$Q_{ll'}$	The distance between places “l” and “l′”
$\tilde{\mu}_m$	The cost of installing a “m” type machine
$\tilde{\pi}_m$	The cost of removing a “m” type machine
$\widetilde{FC}_m$	Cost of “m” type machine overhead in each time period
$\widetilde{VC}_m$	Variable costs of “m” type machine
φ_m	Cost of a “m” type machine purchasing
$Ucap_c$	Maximum number of machines to be assigned to cell c
$Lcap_c$	Minimum number of machines to be assigned to cell c
A_m	A “m” type machine area
$\widetilde{\omega}_{prm}$	Processing time of “r”$_{th}$ “p” type product operation on “m” type machine
$\widetilde{cap}_m$	Time capacity of “m” type machine in each time period
$\widetilde{Tcap}$	Total capacity of the workshop to store products
$Gcap$	Maximum limit for carbon dioxide emissions
V_p	“p” type production’s volume
$\widetilde{OC}_w$	Cost of each working day of the operator with “w” expertise
g_{pm}	The amount of gas emission Co_2 due to the production of each unit of “p” type product on the “m” type machine
$\widetilde{HC}_p$	Inventory cost per unit of “p” type product
SS_p	Maximum “p” type product shortage in each period

g_{pm}	Each type of machine has a specific level of pollution; this emission level is in conflict with the cost of each machine. This means that the less pollution the machine produces, the higher the associated costs. And I_{ph} is also a parameter.
Decision variables	
x_{clmwh}	If the operator with "w" expertise is assigned to a m-type machine at location "l" in cell "c" at time "h", then 1, and otherwise 0
δ_{prmw}	If the first operation of p-type product can be performed on m-type machine by an operator with "w" expertise, then 1 and otherwise 0
S_{ph}	p-type product shortage amount at time h
I_{ph}	p-type product amount at time h
$u_{prclmhw}$	The number of p-type products on which the first operation was performed by the m-type machine at location "l" in cell "c" at time "h" by an operator with expertise "w".
$U_{prcc'll'mm'h}$	The number of p-type products processed at time "h" by the "r"th operation on the m-type machine located at position "l" in cell "c", and now transferred to the m-machine at cell "c" at location "l" to perform the "r+1"th operation. v_{lmh}: If place "l" is empty at time "h-1" or assigned to a machine other than m-type machine, and assigned to m-type machine at h, 1, otherwise 0
v'_{lmh}	If the "m" type machine is assigned to location "l" at time "h-1" and removed at time "h", or replaced by another machine, 1 and otherwise 0
N_{mh}	The total number of "m" type machines that are added to the workshop at the beginning of "h" period.
NO_{wh}	Number of operators available with "w" expertise at workshop at time "h"

In many articles to write a mathematical model, the same letters are used to represent more than one parameter in the writing of parameters and decision variables (Khanchehzarrin et al., 2021; Shahmizad et al., 2021). Not all parameters and decision variables need to be displayed in different letters, but in GAMS software, these letters are written differently. For example, for those two decision variables in GAMS, we used "u" for one and up for the other. For two parameters, "i" and "ii" are used in the software.

Objective functions

$$\boldsymbol{Min\ Z_1 = \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{\substack{c'=1\\c\neq c'}}^{C}\sum_{l=1}^{L}\sum_{l'=1}^{L}\sum_{m=1}^{M}\sum_{m'=1}^{M} U_{prcc'll'mm'ww'h}\times Q_{ll'}\times \widetilde{E}_p + \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{l'=1}^{L}\sum_{m=1}^{M}\sum_{m'=1}^{M} U_{prcc'll'mm'ww'h}\times Q_{ll'}\times \tilde{I}_p + \sum_{h=2}^{H}\sum_{l=1}^{L}\sum_{m=1}^{M} v_{lmh}\times\tilde{\mu}_m + \sum_{h=2}^{H}\sum_{l=1}^{L}\sum_{m=1}^{M} v'_{lmh}\times\tilde{\pi}_m + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} x_{clmwh}\times \widetilde{FC}_m + \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} u_{prclmwh}\times\tilde{\omega}_{prm}\times\widetilde{VC}_m + \sum_{h=1}^{H}\sum_{m=1}^{M} N_{mh}\times\varphi_m + \sum_{h=2}^{H}\sum_{l=1}^{L}\sum_{m=1}^{M} x_{clmw1}\times\tilde{\mu}_m + \sum_{h=1}^{H}\sum_{p=1}^{P} I_{ph}\times\widetilde{HC}_p + \sum_{w=1}^{W}\sum_{h=1}^{H} NO_{wh}\times\widetilde{OC}_w} \tag{1}$$

$$Min\ Z_2 = \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} u_{prclmwh}\times g_{pm} \tag{2}$$

$$Min\ Z_3 = \sum_{h=1}^{H}\sum_{p=1}^{P} S_{ph} \tag{3}$$

Constraints

Subject to:

$$u_{prclmwh} \le x_{clmwh}\times\delta_{prmw}\times\widetilde{D}_{ph} \qquad \forall\ p,r=\{1,\dots,R_p\},c,l,m,w,h \tag{4}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W}u_{prclmwh}+I_{p,h-1}+S_{ph}-I_{ph}=\widetilde{D}_{ph} \qquad \forall p, r=R_p, h \tag{5}$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{w=1}^{W}x_{clmwh}\leq 1 \qquad \forall l, h \tag{6}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W}x_{clmwh}\times A_m\leq Ucap_c \qquad \forall c, h \tag{7}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W}x_{clmwh}\times A_m\geq Lcap_c \qquad \forall c, h \tag{8}$$

$$\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{w=1}^{W}u_{prclmwh}\times\omega_{prm}\leq \widetilde{cap}_m \qquad \forall l, m, h \tag{9}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W}U_{prcc'll'mm'h}=u_{p,r+1,c'l'm'w'h} \qquad \forall p, c', l', m', w', h, r=1,\dots,R_p- \tag{10}$$

$$\sum_{c'=1}^{C}\sum_{l'=1}^{L}\sum_{m'=1}^{M}\sum_{w'=1}^{W}U_{prcc'll'mm'h}=u_{prclmwh} \qquad \forall p, c, l, m, w, h, r=1,\dots,R_p-1 \tag{11}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{w=1}^{W}x_{clmw,h+1}-\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{w=1}^{W}x_{clmwh}=N_{m,h+1} \qquad \forall m, h=1,\dots.,H-1 \tag{12}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{w=1}^{W}x_{clmw,1}=N_{m,1} \qquad \forall m \tag{13}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}x_{clmwh}=NO_{wh} \qquad \forall w, h \tag{14}$$

$$\left(1-\sum_{c=1}^{C}\sum_{w=1}^{W}x_{clmwh}\right)\times\sum_{c=1}^{C}\sum_{w=1}^{W}x_{clmw,h+1}=v_{lm,h+1} \qquad \forall l, m, h=1,\dots,H-1 \tag{15}$$

$$\sum_{c=1}^{C}\sum_{w=1}^{W}x_{clmwh}\times\left(1-\sum_{c=1}^{C}\sum_{w=1}^{W}x_{clmw,h+1}\right)=v'_{lm,h+1} \qquad \forall l, m, h=1,\dots,H-1 \tag{16}$$

$$\sum_{p=1}^{P}I_{ph}\times V_p\leq\widetilde{Tcap} \qquad \forall h \tag{17}$$

$$\sum_{p}^{p=1}\sum_{r=R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W}u_{prclmwh}\times g_{pm}\leq Gcap \qquad \forall h \tag{18}$$

$$I_{p,0}=0 \qquad \forall p \tag{19}$$

$$\sum_{h=1}^{H}S_{ph}\leq SS \qquad \forall p \tag{20}$$

$$S_{ph}\leq SS_p \qquad \forall p, h \tag{21}$$

x_{clmwh} δ_{prmw} v_{lmh} v'_{lmh} $binary\ variable\ else$ ≥0

Equation (1) is the first objective function, which is to minimize costs. It is considered an economic objective function that each component has the cost of products transferring between cells, the cost of transferring products inside cells, the cost of machines' installation, the cost of removing machines, the variable's overhead cost, the variable cost, respectively. Machinery per operating time, cost of purchasing machinery, cost of installing machinery in the first period, cost of maintaining products in the workshop warehouse, and the last component is the operator's cost per period. Equation (2) is the second objective function. It is also introduced as an environmental objective function to minimize Carbon gas emission by any machines per goods production unit. The welding process is widely used in the production process. The gases used in welding such as carbon dioxide and argon that have an adverse effect on the environment. High electric currents cause ozone, nitric oxide and nitrogen dioxide. The presence of nanoparticles is more harmful to humans than large particles diffusion of nanoparticles occurred in welding. Therefore when measuring emissions, a certain amount of material produced per unit of time is measured (Hammad et al., 2021). Equation (3) as a third objective function is to minimize the lack of customer demand, which conveys the concept of increasing customer satisfaction, and the same objective function is called social responsibility. In this study, it is assumed that customer satisfaction is a function of shortage. In this way, the shortage causes customer dissatisfaction. Therefore, the smaller the shortage, the higher the customer satisfaction. Therefore, increasing customer satisfaction leads to increased social responsibility toward customers. Equation (4) states that the relevant machines and operators can produce products to the maximum demand in each period. There must also be the ability to produce the desired product by the assigned machine and operator. Equation (5) demonstrates the level of workshop warehouse inventory, also the lost opportunity to supply the product (shortage) at any time for each type of product. It states that each period's product produced amount plus the shortage and previous period's inventory should be equal to the amount of demand plus inventory of this period. Equation (6) express that each location in each period can be assigned to a maximum of one machine. This equation indicates the spatial importance of the cells. Equation (7) shows the maximum capacity of the cell to accommodate the machines. Equation (8) is similar to equation (7) except that it shows the minimum number of machines that must be placed in each given cell. Equation (9) indicates the time capacity of each machine in each period to produce the product. In other words, each product needs an amount of time to produce, and this equation indicates the allowable amount of each machine's employment in each period. Equations (10) and (11) are current maintenance constraints. In other words, equation (10) ensures that all "p" products that were in location l for operation r and are moving to location l' for operations $r+1$ are equal to all p products at location l that are ready to perform the operation $r+1$. Equation (11) guarantees that all p products that are in location l' for $r+1$ and moved from location l for this operation are equal to all p products were are in location l performing operation r. Equation (12) shows the number of machines added to the workshop area in periods. It shows the number of machines purchased in each period. Equation (13) shows the number of machines purchased in the first period. Equation (14) expresses the number of operators in periods. Equations (15) and (16) indicate the amount of machinery movement or, in fact, the installation and removal of machinery in each period. Equation (17) shows the workshop warehouses capacity to store products after production. Equation (18) is the allowable amount of Co_2 gas emission. Equations (19) and (20) respectively state that the warehouse is empty on day zero and that shortage should not exceed a certain amount. Equation (21) ensures that the shortage of crop p in each period is not more than a certain amount. Constraints 12, 13, and 14 are used to determine the number of machines and operators used. In addition, equation 19 must be because, on day zero, it may fill the warehouse and no longer produce.

B. Constraints linearization

As constraints related to the equations (15) and (16) are nonlinear, they become linear (Bayram & Şahin, 2016).

$$0.5 + v_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} \geq 0 \qquad \forall l,m,h = 1,\dots,H-1 \tag{22}$$

$$1.5 \times v_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} - 1 \leq 0 \qquad \forall l,m,h = 1,\dots,H-1 \tag{23}$$

$$0.5 + v'_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} \geq 0 \qquad \forall l,m,h = 1,\dots,H-1 \tag{24}$$

$$1.5 \times v'_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} - 1 \leq 0 \quad \forall l,m,h = 1,\dots,H-1 \tag{25}$$

There is no variable transformation in the linearization done by the article (Bayram & Şahin, 2016), and linearization has been done as presented above. Because of the simplicity of the data gathering, the fuzzy triangular distribution is used to model the inexact nature of the imprecise parameters of the problem. The linearization of the mathematical model allows the model to be optimized with less iteration. Also, linearization of the mathematical model will reduce the solution time and reduce the complexity of the model.

IV. PROBABILISTIC LINEAR PROGRAMMING MODEL

Philosophically, fuzzy logic expresses a logical concept in which, unlike Aristotelian logic, which rules classical mathematics, it uses multi-valued logic to express its concepts. Unlike Aristotelian logic, which always considers everything deterministic, this logic does not assume a boundary between existence and non-existence. In this logic, anything with a specified amount can belong to a group. An important point from our perspective in this paper is applying fuzzy models to the subject of this article. The complex nature of the DSCM makes its mathematical model parameters uncertain. As mentioned, there are several types of uncertainty, one of which is programming uncertainty, which can be cited when there is insufficient information about the parameters.

Furthermore, since the parameters and information about the DCMS problem are uncertain, fuzzy logic is used for the input information. The Fazli Khalaf research method has been applied to transform the problem's probabilistic model, which includes inaccurate coefficients both in the objective function and constraints, into a deterministic model (Fazli-Khalaf et al., 2017). This method is computationally efficient because it retains the linearity property and does not increase objective functions and inequality constraints. Due to the simplicity of the data, the triangular fuzzy distribution is used to model the inexact nature of the vague parameters of the problem. Suppose that $\tilde{c} = (c^{(1)}, c^{(2)}, c^{(3)})$ is a triangular fuzzy number and the following model is considered:

$$Min\ Z = cx \tag{26}$$

$$s.t{:}\ Ax \leq b$$

$$Dx \geq f$$

$$x \geq 0$$

Now, assuming that x is the decision variable and c, b, A, D and f are the model parameters, and the parameters c, b, and f are fuzzy, then the de-fuzzy model is as follows:

$$Min\ Z = \left[\frac{c^{(1)}+c^{(2)}+c^{(3)}}{3}\right]x \tag{27}$$

$$s.t{:}\ Ax \leq \left[\left(2\alpha-1\right)b^{(1)} + \left(2-2\alpha\right)b^{(2)}\right]$$

$$Dx \geq \left[\left(2\alpha-1\right)f^{(3)} + \left(2-2\alpha\right)f^{(2)}\right]$$

$$x \geq 0$$

The α should take a value between 0.5 to 1. Defuzzification is done based on the Fazli-Khalaf approach (Fazli-Khalaf et al., 2017). C, b, and f are non-deterministic and have a triangular membership function, non-deterministic in the parameter's average objective function. A larger number is also used to satisfy demand in a "greater than or equal to" constraint. The "less than or equal to" constraint, like capacity, the smaller number is the criterion. Just before each fuzzy parameter in the constraint proportional to the "greater- or less than or equal to" inequality, according to Equation (26) there is an expression that performs a sensitivity analysis on fuzzy parameters by changing the coefficient α, which is, in fact, the level of confidence. By increasing the α coefficient from 0.5 to 1, a larger number is multiplied by the pessimistic number; and the closer it gets to 0.5, the more value is multiplied by the number.

Non-deterministic parts of objective functions and all constraints can be determined as follows:

Final De-Fuzzy and linearized model:

(28)

$$
\begin{aligned}
Min\ Z_1 = & \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{\substack{c'=1\\ c\neq c'}}^{C}\sum_{l=1}^{L}\sum_{l'=1}^{L}\sum_{m=1}^{M}\sum_{m'=1}^{M} U_{prcc'll'mm'ww'h} \times Q_{ll'} \times \left[\frac{E_p^1+E_p^2+E_p^3}{3}\right] \\
& + \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{l'=1}^{L}\sum_{m=1}^{M}\sum_{m'=1}^{M} U_{prcc'll'mm'ww'h} \times Q_{ll'} \times \left[\frac{I_p^1+I_p^2+I_p^3}{3}\right] \\
& + \sum_{h=2}^{H}\sum_{l=1}^{L}\sum_{m=1}^{M} v_{lmh} \times \left[\frac{\mu_m^1+\mu_m^2+\mu_m^3}{3}\right] + \sum_{h=2}^{H}\sum_{l=1}^{L}\sum_{m=1}^{M} v'_{lmh} \times \left[\frac{\pi_m^1+\pi_m^2+\pi_m^3}{3}\right] \\
& + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} x_{clmwh} \times \left[\frac{FC_m^1+FC_m^2+FC_m^3}{3}\right] \\
& + \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} u_{prclmwh} \times \left[\frac{\omega_{prm}^1+\omega_{prm}^2+\omega_{prm}^3}{3}\right] \times \left[\frac{VC_m^1+VC_m^2+VC_m^3}{3}\right] \\
& + \sum_{h=1}^{H}\sum_{m=1}^{M} N_{mh} \times \varphi_m + \sum_{h=2}^{H}\sum_{l=1}^{L}\sum_{m=1}^{M} x_{clmw1} \times \left[\frac{\mu_m^1+\mu_m^2+\mu_m^3}{3}\right] \\
& + \sum_{h=1}^{H}\sum_{p=1}^{P} I_{ph} \times \left[\frac{HC_p^1+HC_p^2+HC_p^3}{3}\right] + \sum_{w=1}^{W}\sum_{h=1}^{H} NO_{wh} \times \left[\frac{OC_w^1+OC_w^2+OC_w^3}{3}\right]
\end{aligned}
$$

$Min\ Z_2 = \sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} u_{prclmwh} \times g_{pm}$ (29)

$Min\ Z_3 = \sum_{h=1}^{H}\sum_{p=1}^{P} S_{ph}$ (30)

$Subject\ to$:

$u_{prclmwh*} \leq \delta_{prmw} * \ x_{clmwh} * \left[\left(2\alpha-1\right)D_{ph}^{(1)} + \left(2-2\alpha\right)D_{ph}^{(2)}\right] \quad \forall\ p, r = \{1, \dots, R_p\}, c, l, m, w, h$ (31)

$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} u_{prclmwh} + I_{p,h-1} + S_{ph} - I_{ph} = \left[\left(2\alpha-1\right)D_{ph}^{(3)} + \left(2-2\alpha\right)D_{ph}^{(2)}\right] \quad \forall p, = R_p, h$ (32)

$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{w=1}^{W} x_{clmwh} \leq 1 \qquad \forall l, h$ (33)

$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} x_{clmwh} \times A_m \leq Ucap_c \qquad \forall c, h$ (34)

$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} x_{clmwh} \times A_m \geq Lcap_c \qquad \forall c, h$ (35)

$\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{c=1}^{C}\sum_{w=1}^{W} u_{prclmwh} \times \omega_{prm} \leq \left[\left(2\alpha-1\right) cap_m^{(1)} + \left(2-2\alpha\right) cap_m^{(2)}\right] \qquad \forall l, m, h$ (36)

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} U_{prcc'll'mm'h} = u_{p,r+1,c'l'm'w'h} \qquad \forall p,c',l',m',w',h,r=1,\dots,R_p-1 \tag{37}$$

$$\sum_{c'=1}^{C}\sum_{l'=1}^{L}\sum_{m'=1}^{M}\sum_{w'=1}^{W} U_{prcc'll'mm'h} = u_{prclmwh} \qquad \forall p,c,l,m,w,h,r \tag{38}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{w=1}^{W} x_{clmw,h+1} - \sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{w=1}^{W} x_{clmwh} = N_{m,h+1} \qquad \forall m,h=1,\dots.,H-1 \tag{39}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{w=1}^{W} x_{clmw,1} = N_{m,1} \qquad \forall m \tag{40}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M} x_{clmwh} = NO_{wh} \qquad \forall w,h \tag{41}$$

$$0.5 + v_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} \geq 0 \qquad \forall l,m,h=1,\dots,H-1 \tag{42}$$

$$1.5 + v_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} - 1 \leq 0 \qquad \forall l,m,h=1,\dots,H-1 \tag{43}$$

$$0.5 + v'_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} \geq 0 \qquad \forall l,m,h=1,\dots,H-1 \tag{44}$$

$$1.5 + v'_{lm,h+1} + \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmwh} - \sum_{c=1}^{C}\sum_{w=1}^{W} x_{clmw,h+1} - 1 \leq 0 \qquad \forall l,m,h=1,\dots,H-1 \tag{45}$$

$$\sum_{p=1}^{P} I_{ph} \times V_p \leq \left[(2\alpha-1)Tcap^{(1)} + (2-2\alpha)Tcap^{(2)}\right] \qquad \forall h \tag{46}$$

$$\sum_{p}^{p=1}\sum_{r=R_p}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{w=1}^{W} u_{prclmwh} \times g_{pm} \leq Gcap \qquad \forall h \tag{47}$$

$$I_{p,0} = 0 \qquad \forall p \tag{48}$$

$$\sum_{h=1}^{H} S_{ph} \leq SS \qquad \forall p \tag{49}$$

x_{clmwh} δ_{prmw} v_{lmh} v'_{lmh} *binary variable else* ≥0

V. VERIFICATION AND VALIDATION OF THE MODEL

A small-scale example and its decision variables are examined to validate the proposed model. For the multi-purpose nature of the proposed model, the partial constraint method developed in GAMS software has been used to provide the Pareto frontier for the three objective functions of this model. Information about model parameters is provided in Table 3-1. For example, the number of product types is 2, the number of operations is 3, the number of cells is 2, the number of places for deploying machines is 5, the number of types of machines is 2, the type of specialization of operators is 3, and goods production is done in 4 days. The results of solving the proposed problem by GAMS software and the AEC method, and the Pareto frontiers formed are shown in the following steps.

Based on the two-dimensional Pareto frontier formed by the AEC method, it can be concluded that each of the second and third objective functions is in conflict with the first one, that is with increasing costs separately, the amount of Carbon gas emission is reduced, and the amount of demand shortage is justified by the reduction. In this section, the optimal point (cost = 404310, environment = 19440, social responsibility = 159) is selected for analysis.

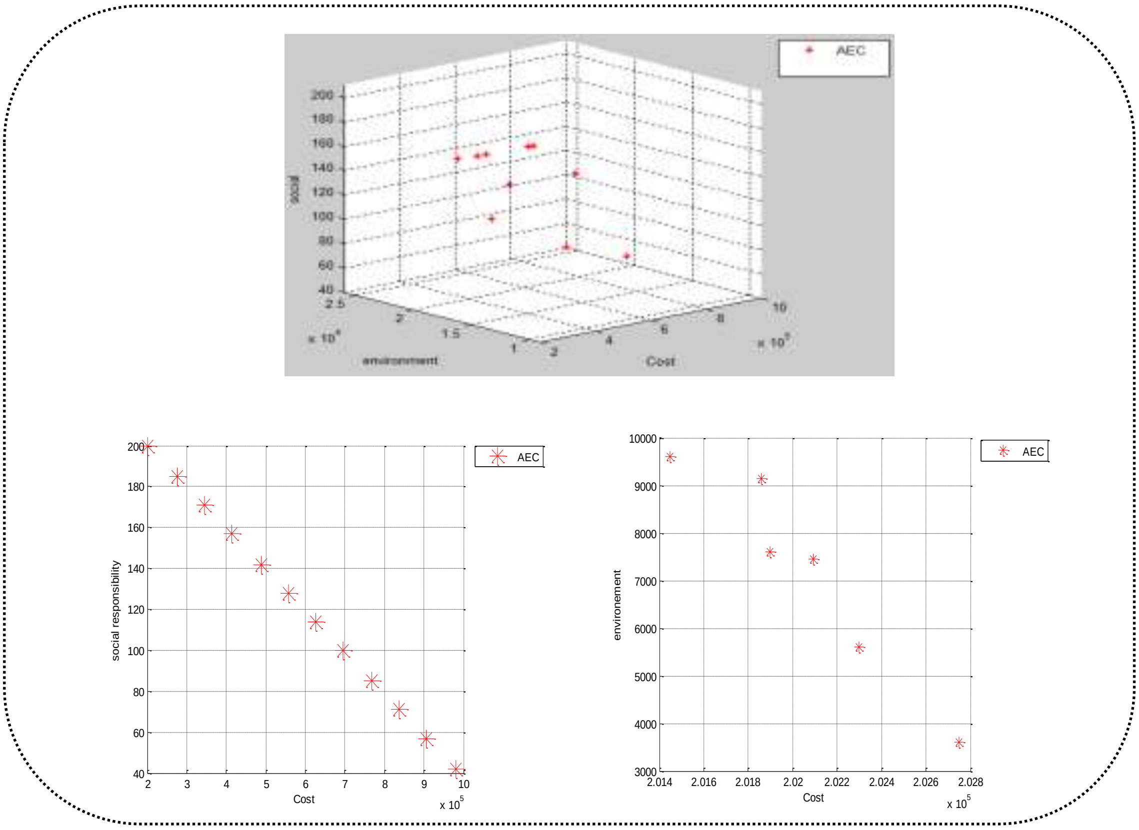

Fig 1. Pareto 3D and 2D frontiers resulting from problem solving for model validation

Table II. Production rate and shortages in each time period

H1	*H2*	*H3*	*H4*
	$u_{1114122} = 15$ $u_{1212132} = 15$ $u_{1314122} = 15$ $u_{2114122} = 30$ $u_{2212132} = 30$ $u_{2314122} = 30$	$u_{1114123} = 6$ $u_{1212133} = 6$ $u_{1314123} = 6$ $u_{2114123} = 30$ $u_{2212133} = 30$ $u_{2314123} = 30$	
$S_{11} = 30$ $S_{21} = 30$	$S_{12} = 15$ $S_{22} = 0$	$S_{13} = 24$ $S_{23} = 0$	$S_{14} = 30$ $S_{24} = 30$

Also, GAMS software can solve problems 1 to 4, and subsequent problems are almost unsolvable due to a significant increase in solution time; this issue as well as the expression of the complexity of this problem by other authors is also a proof of problem’s NP-hard nature.

Table III. EC output from GAMS

Problem	*EC*					
	TIME	*Diversity*	*Spacing*	*MID*	*SNS*	*RAS*
3*2*2*2*2*2*2	28.325	933735.6	8651.32	346891.3	262690.9	0.434458
3*2*2*3*2*2*2	98.253	1435971	10806.49	599537.5	398912.9	0.541494
3*3*3*4*3*3*3	445.322	3450477	25744.29	1957360	1008439	0.009642
3*3*3*5*3*3*3	1328.328	4784494	35829.16	2553033	1380232	0.069407

VI. MULTI-OBJECTIVE GENETIC META-HEURISTIC ALGORITHM

A. NSGA-II

As mentioned, with the advancement of modeling and the enlargement of problems, problems became NP-hard, and researchers had to find new ways to solve them. Therefore, some researchers considered the real world as a problem that automatically solves this problem. Therefore, researchers took ideas from existing natural phenomena and designed different solutions, and the name of these methods is a testament to the original origin of the idea, such as genetic algorithm, beehive algorithm, ant colony algorithm, and alike. In the following section, the NSGA-II algorithm is applied to solve the proposed model. Also, to correctly understand the algorithm code, the solved problem in the previous chapter as a model validation is solved in this chapter with a multi-objective genetic algorithm.

A.A. Responses' representation

A string of decimal numbers has been employed to show the response to this problem.

The response display consists of 5 parts.

The first and second sections are for determining the machine and operator located in each cell in each position, in each period. Therefore the length of each section is equal to $c \times h \times l$, where c is the number of cells, h is the number of periods, and l is the number of locations within each cell.

The following equations are utilized to map the decimal number of the algorithm to the answer number:

$$(response\ number * (machine) + 1)$$

$$(response\ number * (operator) + 1)$$

After settling on devices' location, operators in the cell, and position in the period, it must be determined to respond to each period's demand that how much of demand is from production and how much is provided by previous period inventory. The shortage must also be clarified. To this target, we use the third and fourth parts of the response representation.

The lengths of the third and fourth parts are equal to $p * h$; h is the number of periods and p is the number of goods' types.

To map the decimal numbers of the algorithm to the answer to the problem, we use proportionality by first considering the fraction of demand specified in the fourth section of the answer as a shortage. Now the demand that must be met in each period has been determined.

machine determination	0.17	0.71	0.03	0.28	0.05	0.10	0.82	0.69	0.32	0.95	...
operator determination	0.03	0.44	0.38	0.77	0.80	0.19	0.49	0.45	0.65	0.71	...
shortage determination	0.75	0.28	0.68	0.66	0.16	0.12	0.50	0.96	0.34	0.59	...
inventory determination	0.22	0.75	0.26	0.51	0.70	0.89	0.96	0.55	0.14	0.15	...
sharing demand among machines & operators	0.81	0.91	0.13	0.91	0.63	0.10	0.28	0.55	0.96	0.96	...

Fig 2. responses' display

Each product manufacturing amount in each period and the part required from the previous period is determined from the last period to the first. Going back to a previous period, what should be considered for the next period is the demand of that period, the total demand of that period, and inventory. Again, using the displayed answer number, the total production level and the inventory provided amount will be determined.

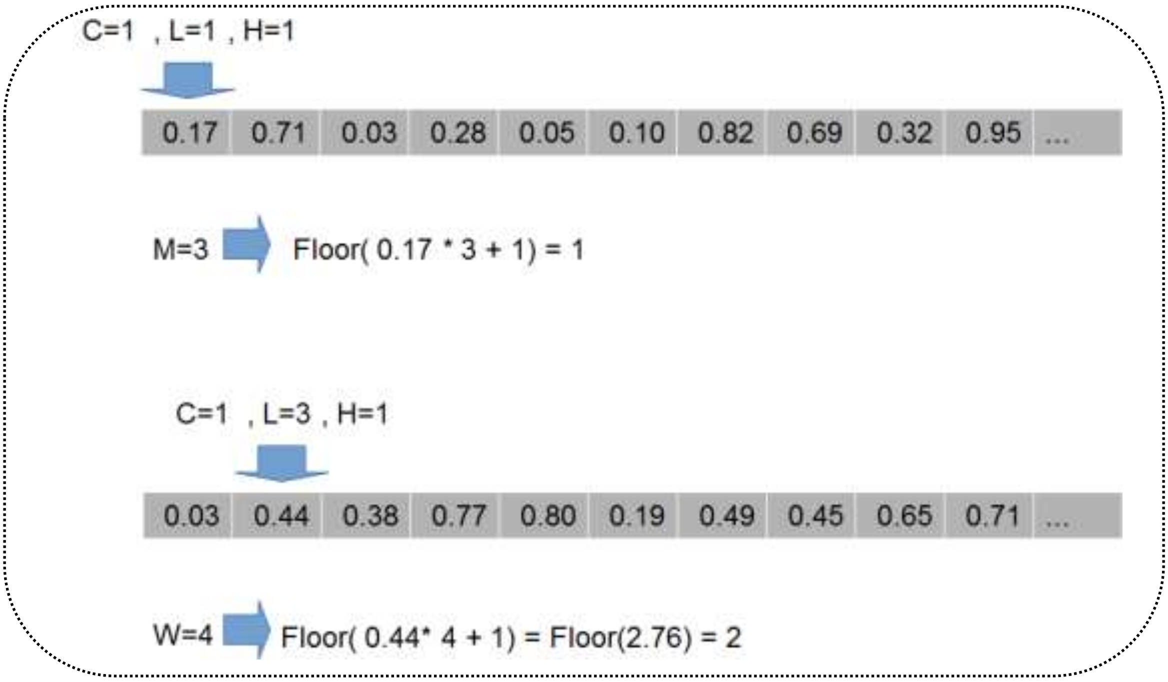

Fig 3. Indication of machine and operator numbers' determination

The same procedure is followed until the first period. We do not have inventory in the first period of preparation. That is, the inventory at the beginning of the first period is zero.

After determining the amount of each product manufactured in each period, we must determine on which machine each amount of production will be done; for this section, we use the last section of the answer display. In this section mapping, the decimal number of the answer in each period determines each machine's share that is capable of operating on that product. For example, three machines with an operator assigned to them can perform r operations on a p-piece; the final demand of that period (including shortage and inventory) is 40, and the number of answers corresponding to these three machines is 0.2, 0.3, and 0.5, in the case of the 8, 12, and 20 units are production amounts related to first, second, and third machines.

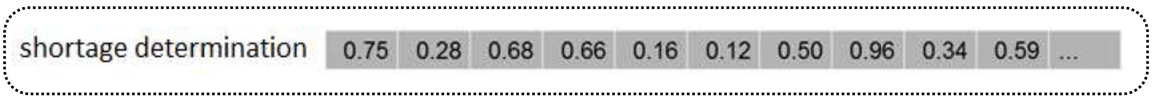

Fig 4. shortage amount indication

A.B. MOPSO

Moore and Chapman (1999) provided an algorithm for solving multi-objective problems using the PSO method. This algorithm is called Multi-Objective Particle Swarm Optimization (MOPSO). In the MOPSO algorithm, in addition to storing the Pareto front values, the values of local Pareto solutions of each particle are also stored. In fact, the best location for each particle remains until the solution is improved.

```
Begin
    Initialize swarm positions, velocities and
leaders.
    Send leader to archive
    Crowding (leaders), g = 0
    While g < gmax
        For each particle
          Select leader.
          Update position (flight) and velocities.
          Mutation.
          Evaluation.
          Update pbest.
        EndFor
        Update gbest (leaders)
        Send leaders to archive.
        Crowding (leaders), g = g+1
    EndWhile
    Report results in archive
End
```

Fig 5. MOPSO pesocode

The proposed movement method for this research is defined as follows:

$$V_t = (C_0 * V_{t-1}) + \left(C_1 * rand(SPX_t - X_t)\right) + \left(C_2 * rand * (SGX_t - X_t)\right) \tag{50}$$

In which SPX_t is the selected solution from personal Pareto fronts in iteration t, X_t is equal to the current locations of particles, $SGX_t$is in the form of selected solutions from Pareto's front in iteration t and V_t is the velocity vector at iteration t.

Table IV. Parameters of the MPSO algorithm

Number of iteration	$\boldsymbol{T_{max}}$
Number of particles	$\boldsymbol{Na = 50}$
Inertia weight	$\boldsymbol{C_0 = 0.6}$
Cognitive (local) accelerator constant	$\boldsymbol{C_1 = 0.6}$
Social (global) accelerator constant	$\boldsymbol{C_2 = 0.7}$

B. Analysis of results and data

As stated at the beginning of this section, the problem solved in the previous section is first solved with the proposed algorithm, and the relevant Pareto frontier is shown. It is then represented by "α" s with different values of change in objective functions. Finally, the results are presented by statistical analysis in Minitab software.

C. Responses' feasibility

In the meta-heuristic algorithm, three methods can be used to apply constraints and create a feasible response. The first method is to create a feasible response in the response display itself so that no impossible response can be generated, such as creating a permutation. In the second case, by calculating and applying the parameters, we map the algorithm response to a feasible solution. For example, in this article, for each response related to the device, before mapping, we consider the list of devices that can be done according to other parameters and select them from the mapping calculations. That is, dynamically mapping the response display only allows feasible responses. The third way to apply constraints is to use a penalty. It is used for constraints that cannot be applied from the first two methods. Because of the sensitivity in determining the penalties' type and amount, this method application has always been tried to be limited. In this paper, the problem is coded in meta-heuristic algorithms using the second method and the mapping described above since the response display uses a continuous string. Considering the similarity of the frontiers created in the algorithm, the exact solution method of the model, and the sensitivity analysis on the alpha variable, the performance as expected by the algorithm can be concluded.

D. Proximity

Since the algorithm works with serial numbers, and the continuous response is mapped to a scalable response, we can use the usual continuous operators.

E. Output of multi-objective algorithms

Table V. multi-objective Genetic algorithm results

Methods	*NSGA-II*	*MOPSO*
First objective function	151865.33	151897.14
Second objective function	4440	4479
Third objective function	260	279
Total shortage	260	276
Total S_{ph} shortage	0 0 18 15 7 3 3 6 0 0	0 0 23 26 7 3 5 9 0 0
Total I_{ph} shortage	0 0 16 18 0 0 28 13 30 0	0 0 15 25 0 0 28 18 32 0

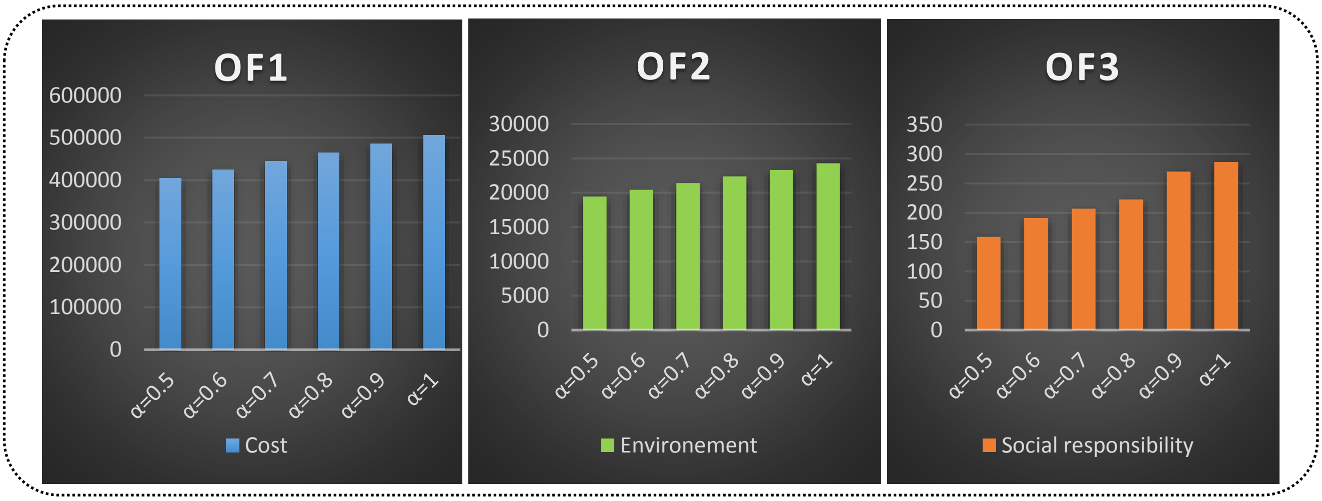

Fig 6. α sensitivity analysis

As is evident, with increasing α, due to the increasing effect on the pessimistic value of fuzzy parameters and the nature of minimizing the objective functions, they increase with value. Thus, with an increasing demand for products, the cost of installation, purchase of machinery, fixed and variable production costs, costs, carbon dioxide emissions, and shortages increase.

VII. STATISTICAL ANALYSIS

A. Adjusting the parameter by the Taguchi method

The Taguchi method has two significant advantages, firstly, it does not need to examine all possible tests for factors, and only a certain fraction of the tests are examined. Secondly, a suitable amount of information is extracted from the examined fraction, and adjusting factors use relatively good information. In the Taguchi method, the factors affecting the test result are divided into two categories: uncontrollable (called noise (N)) and controllable (called signal (S)). An S/N variable is then defined, which is the signal-to-noise ratio. The Taguchi method of parameterization adjusts the factors to levels that maximize the S/N ratio. One of the meta-heuristic methods used in this research is the NSGA-II algorithm; four parameters MaxIt, NPOP, PC, PM must be set at optimal levels. For this purpose, first, three levels of low (1), medium (2), and high (3) are defined separately for each parameter to solve the problems, which are given in tables (1-4). Then, the proposed set of experiments of the Taguchi method is calculated for four factors in three levels, in which nine different modes are designed. (It should be noted that each experiment is performed ten times, and their average is recorded, which is done to reduce the algorithm's error, and the response will be more reliable).

Table VI. Defined Levels for Genetic Algorithm Parameters in Problem Solving

Parameter/GA agent	*Low level (1)*	*Low level (2)*	*High level (3)*
Max it	100	200	300
Npop	50	100	150
PC	0.7	0.75	0.8
PM	0.2	0.25	0.3

Table VII. The result of the NSGA-II and MOPSO algorithms to solve the experimental problems

NSGA-II				
Diversity	*Spacing*	*MID*	*SNS*	*RAS*
262411.6	4932.397	1113152	93419.74	0.0155524
276063.1	2890.292	1106130	101846.7	0.00567178
283473	3152.756	1108261	102560.4	0.01020584
18878.43	1120.45	28507.71	5710.82	0.00504784
273985.1	2741.685	1099132	98982.19	0.0189024
271092.2	3364.764	1080016	97562.82	0.00809704
269111.8	5578.681	1102400	93784.79	0.01452906
11772.51	518.1421	16468.93	2719.395	0.00309992
267416.7	2260.451	1074278	95141.67	0.00815334
MOPSO				
Diversity	*Spacing*	*MID*	*SNS*	*RAS*
262410.1	4933.25	1113157	93454.1	0.0155547
2760632.10	2895.241	1106133	101849.0	0.00567194
283454	31529.721	1108276	1025604.2	0.01020599
1887862.1	1121.40	28507.79	57103.4	0.00504793
27398577.2	2744.41	1099139	98989.1	0.0189225
271062.7	33646.710	1080018	97564.01	0.00809809
26911108.7	55789.000	1102402	93786.22	0.01452988
1177263.2	519.7984	164689.91	2719.71	0.00309994
267408.1	2268.4565	1074298	95145.14	0.00815349

As can be seen, the NSGA-II algorithm performed better than the MOPSO algorithm. Therefore, the results are then analyzed on the NSGA-II approach. All the indicators will be converted into one response to create an output from each experiment using the following method. First, the nature of each index based on negative (the less – the better) or positive (the more - the better) must be determined. In this case, the higher the diversity index, the better, and other indicators are negative in nature. Table 8 demonstrates the different indicators and positions that are the same tests designed and defined by O_i.

Table VIII. The nature of the research indicators

	$+$	$-$	$+$	$-$
Q_i	x_1 ($Diversity$)	x_2 (MID)	x_3 (SNS)	x_4 (RAS)
$Q1$	r_{11}	r_{12}	r_{13}	r_{14}
$Q2$	r_{21}	r_{22}	r_{23}	r_{24}
Q_i	r_{ij}	r_{ij}	r_{ij}	r_{ij}

In which the x_j and Q_i represent "j"th and "i"th criterion, respectively. Also, r_{ij} is equal to the amount that "i" will have for "j" indice.

The obtained values of the indices are normalized according to the fuzzy unscaling technique in equations (3-4) and (4-4), which table (3-4) shows the normalized indices.

$$x_j^+ \to R_{ij} = \frac{\mathrm{r_{ij}} - \min(\mathrm{r_{ij}})}{\max(\mathrm{r_{ij}}) - \min(\mathrm{r_{ij}})} \tag{51}$$

$$x_j^- \to R_{ij} = \frac{\max(\mathrm{r_{ij}}) - \mathrm{r_{ij}}}{\max(\mathrm{r_{ij}}) - \min(\mathrm{r_{ij}})} \tag{52}$$

In this method of normalization, indicators with a negative nature will have a positive nature. The indicators are prioritized using the goal programming approach, and according to their importance and weight, each indicator is considered accordingly. In this article, the importance of each weight is applied according to Julai et al. (2013). Then, based on the importance coefficients, the total weight of the indicators of each experiment in the Response equation is calculated.

$$Response = \sqrt[2]{(MID)^2 + (RAS)^2 + (SNS)^1 + (SNS)^1 + (Diversity)^1 + (Spacing)^1} \tag{53}$$

Now, according to the response values of each algorithm, the $\frac{S}{N}$ rate is calculated and the levels of each input parameter are determined based on it. To do this, the resulting response is presented as the final response to the experiments, and "the more- the better" Taguchi formula is used to calculate the S / N ratio.

Table IX. Response values for the NSGA-II algorithm

response	1.7065	2.0471	1.9448	1.6474	1.8585	1.9391	1.6876	1.7321	1.9779

Table X. Result of parameterization of NSGA-II algorithm by Taguchi method

PM	***PC***	***npop***	***Max it***
0.25	0.75	150	100

Table XI. The result of the genetic algorithm for solving experimental problems

Diversity	***Spacing***	***MID***	***SNS***	***RAS***
63323.11	3960.83808	1230081	18021.90326	0.04733198
213232.2	16721.04362	1153510	79167.96964	0.0855734
222972.3	3630.69682	1121447	75716.46116	0.059063
186218.5	14759.14624	1149699	61225.10866	0.05123214
216219.2	5913.73366	1112276	70609.80658	0.0555768
133120.7	6398.04688	1149101	47989.69016	0.0475978
244014.6	5932.7623	1145505	84193.66506	0.0518052
167381.2	11021.57328	1159623	56814.64902	0.0596388
197129.4	7221.26744	1106404	70157.69092	0.0380682

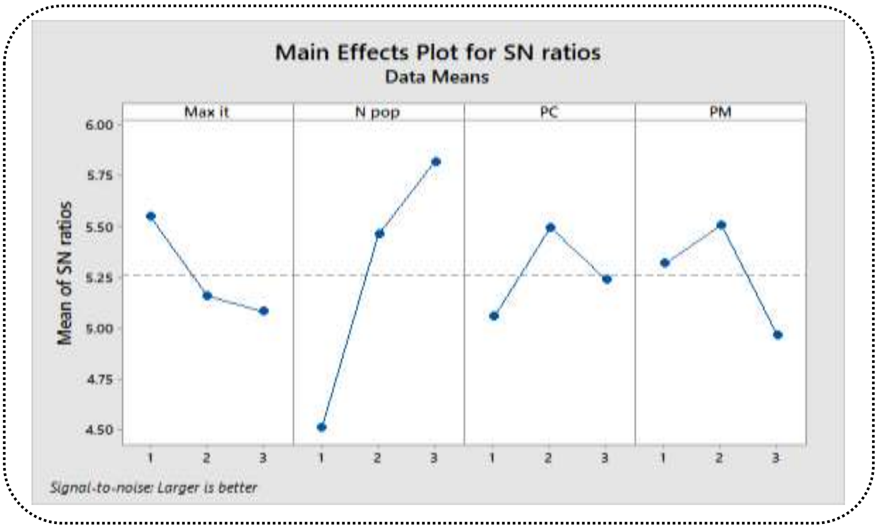

Fig 7. Mini-tab software output for setting parameters of NSGA-II algorithm by Taguchi method

VIII. CONCLUSION

Dynamic cellular manufacturing systems in a competitive environment are essential in producing high-quality goods and diversity. With increasing competition among manufacturers, the movement of production unit managers towards sustainability and its concepts, including economic, environmental, and social dimensions, in their production activities' headlines is vital. The present study aimed to consider the concepts of dynamic cellular manufacturing and sustainable production. Sustainable production is the manufacturing of goods produced through economic processes that minimize negative environmental impacts while saving energy and natural resources and increasing employee satisfaction, community safety, and product health. Sustainable production has economic, social, and environmental dimensions. Each dimension has sections, and each section has criteria that are mentioned earlier. Cellular manufacturing systems are among the new production methods used today in most large production centers with relatively high product diversity and multi-purpose facilities. In this regard, in this paper, the aim was to present a dynamic and sustainable integrated mathematical model considering fuzzy uncertainty under a case study in scaffolding production. In this paper, a three-objective mathematical model was stated, in which the first goal was economic (cost), the second was environmental (air pollution), and the last one was social (responsibility).

All three goals were minimized. The model had 14 assumptions and 17 constraints, and fuzzy product demand. The model was solved for the example taken from the actual manufacturing world (production of safe scaffolding with all three dimensions of sustainable production) by GAMS software through the detailed augmented epsilon-constraint (AEC) method. Meta-heuristic algorithms were used to solve the model due to the NP-hard nature of the model. The NSGA-II and MOPSO algorithms were employed to solve the proposed model due to the problem's high complexity, t. As the results show, the NSGA-II algorithm performed better than the MOPSO algorithm. Therefore, the results are then analyzed on the NSGA-II approach. Algorithm results produce the Pareto frontiers close to the exact method's Pareto frontiers, the same as the augmented epsilon constraint (AEC). A sensitivity analysis on "α" was performed, and we increased the α value step by step; As α raises because of the effect on pessimistic values of the fuzzy parameters and the nature of the minimization of the objective functions, these functions also increase with value. With an increasing demand for products and growing cost of installation and purchase of machinery, fixed and variable production costs, costs, carbon dioxide emissions, and shortages increase. Finally, we statistically analyzed the meta-heuristic algorithm; first, using parameter adjustment by the Taguchi method, four parameters of MaxIt, NPOP, PC, and PM were set for the algorithm at optimal levels. Five indicators are acquired from practical problems' results, and the output of the mini-tab software for adjusting the two algorithms' parameters was shown by the Taguchi method. Finally, according to the field's literature, the present study has similarities in terms of sustainable production criteria compared to previous studies, which are very few. Of course, the difference between this article and previous ones considers three social, economic, and environmental criteria simultaneously. In this research, we used a meta-heuristic algorithm that is not present in the research. In the end, this study is one of the first works in the field of dynamic and sustainable cellular manufacturing. As there was no official database for some parts of cost elements, the experts' estimations were asked to help. The questions about the inventory, installing costs and the estimated uncertain costs have been entered into the mathematical model. Also, the final solution in NSGA-II and MOPSO algorithms depends on the coder's skill in defining chromosomes and the initial value of its parameters. Hence, it can be expanded in various ways to enrich the literature. For example:

The social, economic, and environmental dimensions each have thousands of criteria; as a result, there is much room for research. The concept of sustainable production is one of the newest concepts in production systems and is not limited to manufacturing industries, and research conducted in recent years confirms this. As mentioned in the literature review, these concepts are implemented in all public and private departments in developed industrial countries and monitor their proper application. It is suggested that an institution be established in Iran or a department in every organization and production unit to help institutionalize these concepts while researching in this field and stating the required instructions. The existence of different production methods can include the dimensions of sustainable production and offer its benefits. Also, other meta-heuristic methods can be utilized to solve the model. Profitability can also be included in the objective function. Also, the proposed model can be solved without sustainable goals, and the results can be compared with the proposed method. Finally, the along with the location planning of depots plays a significant role in the cell manufacturing.

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