MULTI-OBJECTIVE ROUTING AND SCHEDULING IN FLEXIBLE MANUFACTURING SYSTEMS UNDER UNCERTAINTY

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Abstract. The efficiency of transportation system management plays an important role in the planning and operation efficiency of flexible manufacturing systems. Automated Guided Vehicles (AGV) are part of diversified and advanced techniques in the field of material transportation which have many applications today and act as an intermediary between operating and storage equipment and are routed and controlled by an intelligent computer system. In this study, a two-objective mathematical programming model is presented to integrate flow shop scheduling and routing AVGs in a flexible manufacturing system. In real-life problems parameters like demand, due dates and processing times are always uncertain. Therefore, in order to solve a realistic problem, foregoing parameters are considered as fuzzy in our proposed model. Subsequently, to solve fuzzy mathematical programming model, one of the most effective technique in the literature is used. To solve the problem studied, two meta-heuristic algorithms of Non-dominated Sorting Genetic Algorithm-II (NSGAII) and multi-objective particle swarm optimization (MOPSO) are offered that the accuracy of mathematical models and efficiency of algorithms provided are assessed through numerical examples.

1. Introduction

Today, due to competitive market conditions, organizations should seek to increase their performance and optimize their manufacturing operations for maintenance and survival in the market. This is why they have to consider so many different factors in order to optimize their scheduling and meet the demands of their customers. Such conditions encourage companies to move from discrete programming to integrated planning. Using integrated programming systems, they can quickly respond to changes and provide products with higher quality and lower production costs. Along with the formation of the concept of integration, integrated manufacturing systems were developed to help companies to give services at a higher level to overcome rivals in today's turbulent market [37, 38, 18].

Scheduling is one of the most significant issues has always been of interest for researchers in production planning. Scheduling can also be defined to determine the sequence and allocate customer orders to the existing production resources (including personnel, machinery, tools, etc.) in order to perform a set of related

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operations at a certain time [43]. Scheduling is usually done with respect to goals such as achieving the promised deadlines, minimizing the floating time, minimizing completion time, and work in process inventory, minimizing power consumption, maximizing output,and more exploitation in work centers. It is noteworthy that most of these goals are contradictory. As noted, the importance of the sequences of jobs on a group of machines focusing on costs and revenue is an important concern because in today's business environment, competition among manufacturing companies is determined through their ability to rapidly respond to rapid changes in the field of trade and producing products with higher quality. Manufacturing companies are trying to acquire these capabilities through automation and creative concepts such as flexible and due manufacturing. These concepts have helped many companies to gain economic profit.

On the other hand, manufacturing activities and processes in various manufacturing systems lead to inevitable flows and movements such as raw materials and job in process and final products among different sectors and parts. Hence, requirements such as transportation equipment in manufacturing systems are needed to transport, manage and organize these flows. That is referred to as material handling systems [59]. Given that material handling systems in manufacturing systems are accounted for a significant proportion of production costs, if such systems are effectively and efficiently implemented, the total cost of production will significantly be reduced. Given the simplicity of manufacturing processes and using creativity and gravity in the past, most transportations in manufacturing systems were nicely done; however, today, due to the complexity generated in manufacturing processes and the need for activities like rework, manufacturing scheduling, information management and so forth have brought about significant changes in such systems and necessitated the use of automation in logistic systems.

Automated Guided Vehicle (AGV) is a kind of material handling equipment that follows a guided rout without operator, with the help of optical or laser electromagnetic automated handling equipment. Because of their highly flexibility, these vehicles are used in large volumes to handle work in process materials in flexible manufacturing systems. The vehicle has also wide applications in warehouses and container terminals and transport systems [19]. It is noted that these vehicles are used for horizontal handlings. In fact, the emergence of AGV goes back to 1955 [39]. Since then the use of this equipment has been developed a lot and had many different applications in the industry. Therefore, in order to meet these diverse applications, their diversity has also increased. Due to the variety of AGVs, they can be used in indoor and outdoor manufacturing systems. Research shows that by 2000, more than twenty thousand AGVs were used in industrial applications [64]. Another use of the equipment is its use in stock and specifically in cross stocks. In the way that AGVs are used in such stocks in order to move pallets between the receipt, storage, sorting and the transport region. In addition, AGVs are also used in shipping containers in ports in shipment area. AGV's have capabilities in transport outside the factory too. For example, they can be used at airports [65].

Clearly, the features of AGVs are different in each of the mentioned cases depending on the environment they are used in, for example, the capacity of one

AGV should be at least 40 ton in moving containers at ports. In cross storages, this capacity is much lower than that in ports and in manufacturing systems, it is generally less than that in storages. On the other hand, AGV systems are highly flexible compared to conveyors and other equipment to transport materials, hence they can be adapted to new conditions for variable conditions of the rate of production, type of product or manufacturing processes by low cost and without the need for a lot of changes. This would not be simply possible for other transportation systems and requires spending high costs to adapt to new conditions. Another advantage of AGV systems is productivity, product quality and safety [67].

As it was pointed out, one of the most important issues in programming manufacturing systems is manufacturing scheduling. In such matters, objectives are generally based on the efficient utilization of resources, rapid response to demand, strict compliance, and appointed deadlines. An efficient and appropriate schedule leads to increase profitability, reduce costs, reduce the time required for completing activities and earn the trust of consumers. In most service companies and manufacturing factories, providing customer orders or servicing is important in a timely manner. Late fees not only affect customers, but also reduce the credit of service companies or manufacturing factories. Thus, attention to scheduling problems on many management issues and planning principles is of great importance. Depending on the volume and specifically diversity of customer orders for products, production systems associated with them will have different characteristics. For example, in flow shop scheduling, each customer order has its own production operations and sometimes need to pass manufacturing processes on some or all machines in production system. Thus, each order has a different manufacturing rout with each other. In addition, the operation time of each of these orders on each of the generating stations can be distinguished from each other [11]

In this regard, one of the topics that are of interest to a significant number of researchers is to minimize the cycle time. However, in most of the research conducted in this field, the time required for the movement of parts between different machines is ignored. The intended rationale for this is that transfer time to the processing time is negligible and therefore they are ignored. However, in recent research conducted in the field, scholars believe that such time is considerable and can affect the optimal solution. Thus, recent research has tried to consider transport time between different workstations in modeling manufacturing systems. For this kind of handling, different vehicles are available for transport. For instance, forklifts, conveyors, cranes or AGV can be used for this purpose. Depending on which of the equipment is used, several issues have emerged and each has their own specific requirements. However, as mentioned above, given the enumerated reasons, the AGVs are of most interest and use than other equipment [71].

It should be noted that the use of AGVs has various limitations in the planning and scheduling activities in manufacturing systems as well that taking them into account is indispensable. For example, limitations of their non-interference, determination of their motion routs, AGVs' battery recharge, and other restrictions that increase the complexity of their use. Thus, if AGVs are not effectively planned and managed, they can even lead to disable manufacturing systems. For example, when two AGVs clashes along the path marked for them, they can stop manufacturing system and substantially increase the cost of the system [70]. Vahdani (2014) proposed two mathematical models for vehicle positioning in a cell manufacturing system where travel time between cells and cost parameters are uncertain. Vivaldini et al., (2016) presented an approach for the prediction the minimum number of AGVs required to implement a given transportation demand within a definite time-window constraint.

It should be noted that in traditional views, controlling and planning manufacturing machinery and transportation systems had been done individually. For example, when developing rules of machinery, the availability of AGVs to determine the priority of doing things was not considered. With this view, it was possible that the job that had the highest priority waits for an AGV in the buffer of a workstation in a long time and at the same time a lower-priority job is transferred to the next station by an unemployed AGV to continue operations. Considering the above, in order to achieve the highest efficiency, coordination and synchronization must be created between workstations and material handling systems.

Based on studies in the literature, it can be found that a significant number of studies have focused on the design of AGV systems independent of manufacturing systems. The goals considered by such studies include determining the number of AGVs and location of picking/delivering stations. In fact, it can be said that these studies have been related to the layout design of the material handling systems. Several studies have also been conducted on in the design of AGV routes that are basically the same design and deployment of the desired topologies [67]. It seems there is dearth of research on the integration of manufacturing scheduling and transportation systems in the literature.

Among the things that can be mentioned in relation to such investigations is that most of the studies have used simulation models and Petri nets for modeling the intended problem and the number of research that has used mathematical programming models for this purpose is limited [14]. Also, most of these studies have mainly focused on providing solution methods for existing models in the related literature and have not had considerable innovations in the field of modeling. Other points to be mentioned in connection with articles having considered these two issues in the context of a mathematical model is the approach used for modeling [52]. In a significant number of these studies, the models have been considered as two separate phases. Some of the studies have also modeled the intended issues in two stages [24]. One of the problem that some researchers have for this type of modeling is that the optimal solution of integrated consideration of these two issues are not necessarily the answer of the same multi-fuzzy model and the answer cannot be derived from as a total optimal answer. In addition, there is a dearth of research examining the two issues simultaneously in the form of a mathematical model. Thus to present a mathematical model that integrates the two issues and studies them is considered necessary [1].

On the other hand, fuzzy scheduling is a very important research topic not only because of the fuzzy nature of most real-world problems, but also because there are still many open questions in this area. Four important motivations that fuzzy set theory is relevant to scheduling are as follows [20]:

- In the scheduling environment, the information required to formulate an objective function, decision variables, constraints and parameters may be vague or not precisely measurable.
- Imprecision and vagueness as a result of personal bias and subjective opinion may further dampen the quality and quantity of available information.
- A fuzzy scheduling algorithm constructs the real system flexibility and models the uncertainty inherent in real environments.

This notice has led to the development of fuzzy scheduling. The most obvious place to introduce fuzzy concepts for modeling uncertainty in scheduling algorithms is with a tasks operation and due date time. Typical scheduling algorithms assume this information to be crisp value; this may or may not be reliable. By modeling these times of a task with a fuzzy number, a system designer can build flexibility into the scheduling algorithm and reach to better solution.

With regard to the cases enumerated it can be said that in this study, routing, scheduling and material handling vehicle constraints have been studied multi-objectively. Also, a mathematical programming model has been proposed for routing automated guided vehicles-manufacturing scheduling in flexible manufacturing systems with regard to manufacturing scheduling and transport system constraints under uncertainty. Moreover, two multi-objective meta-heuristic algorithms have been developed to solve the model. Compared to other studies in the literature, innovations of the current study can be mentioned as follows:

- Providing a multi-objective mathematical programming model for AGV routing in flexible manufacturing systems under fuzzy environment
- Taking into account the restrictions in customers' views that affect manufacturing scheduling
- Providing two multi-objective meta-heuristic algorithms to solve the proposed model

The rest of the paper is organized as follows. Section 2 presents a literature on scheduling and routing in flexible manufacturing systems. Problem definition and formulation are described in Section 3 in detail. The proposed solution approaches are given in Section 4. Computational experiments are provided in Section 5. Finally, the paper is concluded in Section 6.

2. Review of the Related Literature

In this section, we introduce the literature review in three parts. The first part is about scheduling models of transportation systems for transporting materials. The second part is associated with the routing models of transportation system and the third part is dedicated to an integrated model of flexible manufacturing systems that consider manufacturing scheduling and routing decisions of material transport systems simultaneously. It should be noted that transportation system in the review means AGVs. The focus in this section is on the studies that have used mathematical programming models.

Scheduling: On scheduling AGVs, three main categories of issues discussed in the literature can be mentioned. The first is in relation to available capacity of machines to move among different workstations. The second is in connection with the coordination of and scheduling the equipment with other equipment. The final issue is limited space available to stop this machinery. In [48], a problem for AGV scheduling in container terminal was presented in order to minimize existing flow. The model was solved using a new algorithm called NSA+ which is actually the developed simple network simplex algorithm (NSA) in standard mode. Nishi et al., (2011) presented a two-stage decomposition algorithm to solve scheduling and no interference routing problem.

The intended objective function was to minimize the total weight of a set of work delays in a way that a mixed-integer programming model was divided into two levels: high level of the allocation and scheduling of activities and the lower level of routing problem. The main problem was solved using Lagrange relaxation and a lower bound was obtained for the value of objective function. Then by taking two pieces and using analysis method, it tried to close the answer to the initial problem as a lower bound and the answer to the dual problem as an upper bound. Bing (1998), Veeravalli et al., (2002) and Remba et al., (1997) proposed analytical models to schedule AGVs. Sinriech and palni (1998) provided a scheduling optimization algorithm for a routing problem of transport vehicle through multiple loading in a closed loop path over a finite planning horizon. In this study, the arrival and processing times of each job are specified.

Sinriech and Kotlarski (2002) developed the method proposed in the previous study so that they are capable of being used in dynamic mode of the way of loadings. In addition, this study aims at minimize the total displacement times for jobs and number of covered cycles. Hartmann (2005) presented a general model for scheduling material transportation equipment at container terminals. The objective function intended in this study seeks to minimize the average delays of a job and average time for preparation. Meersmans (2001) presented some mathematical models to integrate scheduling automatic transport equipment in container terminals. Also, in order to solve the provided models, detailed methods and innovative algorithms were used.

Meersmans and Wagelmans (2001) provided a mathematical model for integration in scheduling the types of material transportation equipment in container terminals. The objective function considered in this study optimizes the overall performance of terminals through minimizing the duration of the payment activities. This study also developed an innovative method and a branch algorithm and bound to solve the presented model.

Routing: If it has been decided to send AGV for doing activities, appropriate route and schedule should be determined to move AGV from the start point to destination in the network of AGV routes. In fact, a path refers to the directions which an AGV should pass during an existing route network to meet the points of delivery and shipment. An schedule determines the entry and exit times of an AGV from its stop point, times meeting shipment and delivery points and ensures that no collision will happen within travel. So, to choose a route and timing has a significant impact on the performance of manufacturing system. Obviously, the prolongation of the process leads to lower displacement of parts during the planning process. Thus, one of the main objectives of routing AGVs is to minimize the duration of handling equipment.

There are generally two categories for routing AGVs in the literature: static and dynamic algorithms. In routing AGV using static algorithms and a route between i and j points is determined according to a series of restrictions and this path is always used. The main criterion for choosing this path in all static algorithms refers to the shortest route between the two points. However, the disadvantages of these algorithms are the lack of compliance in the event of changes in traffic conditions and system. In dynamic routing, decisions related to routing are made based on real data at any time. Hence, there can be several routes between any two considered points. Ili (1994) examined some general rules and analysis methods in order to design automated material transport systems. In the mentioned study, the main focus has been on automatic transport systems with the capability to be applied in discrete manufacturing systems which are the same AGVs.

These types of systems have many applications in the transportation of parts and materials in small and medium sizes. Also, in this study, material routings have also been studied. Langevin, et al., (1996) provided a dynamic programming method to solve the problem of routing and allocation of AGVs. In the model proposed, the strategy of non-interference in routing has been used. Rajotia et al., (1998a) made a routing strategy that dynamically involved time window constraint as a model. In this study, the concepts of saving motion routes and time window have been used to manage the movement of AGVs. As pointed out above, flexible manufacturing systems include automatic machine tools, automatic material handling systems and automated storage and retrieval requirements. On the other hand, the effective sequence and timing of material transportation systems can have a significant impact on the efficiency of production systems.

Hence, the lack of considering transportation systems is not possible to schedule production systems and transportation systems should be considered among workstations to transport materials and the same time planning should be done for scheduling and routing them and manufacturing equipment. Rajotia et al., (1998b) considered time windows for entry and exit of AGVs to each of the path network nodes of these facilities. In addition, the movement route from AGVs was also examined to visit the nodes. In order to solve the presented model, they used a heuristic algorithm to find the route with the shortest possible time and least intervention among AGVs. Methods offered by Desrochers et al., (1992) and Fisher et al., (1997) have the capability of the optimal solution of the above-mentioned model for a hundred customers. Kohl et al., (1999) provided the capability of solving model to achieve the optimal solution for one hundred and fifty customers using a decomposition algorithm. According to the study conducted by Savelsbergh and Sol (1998), the dynamic routing of movement facilitates has the capability of solution using the branch algorithm and price in the case that this equipment are independent from each. Gans and Van Ryzin (1999) offered a planning model based on classic cover models. Qiu and Hsu (2001) provided an algorithm for routing

AGVs taking into account the constraints of non-interference in a bilateral network in order to minimize the duration of AGVs' travel.

Desaulniers et al., (2003) presented an exact method for routing AGVs in a flexible manufacturing system. The proposed method consists of a greedy search algorithm, column generation methods and cutting and page procedure. It should be mentioned that the performance of the proposed method greatly depends on the quality of primary answer. If the algorithm does not achieve the quality of feasible solution, it will not have the ability to achieve the optimum answer. In addition, when interference is increased among AGVs, the performance of this algorithm is highly reduced. Yoo et al., (2005) provided a simple and easy algorithm to prevent AGVs' stops. The algorithm utilizes graph theory approach. Unlike methods based on Petri Net networks which are very complicated and inflexible, the proposed method can be easily modified for different manufacturing systems. Hence, it has a great usability in planning AGVs in flexible manufacturing systems and distribution centers. It should be noted that this algorithm is composed of two main parts: first, an algorithm acts to prevent AGVs' stops based on graph theory approach and second, deals with routing AGVs. Corra et al., (2007) presented a combined approach for solving the distribution and allocation of AGVs and routing them in a flexible manufacturing system.

The considered problem includes three different decisions including allocation, scheduling and routing AGVs among workstations. The proposed method includes a decomposition algorithm consisting of its main problem as scheduling and its subproblem as routing. On the other hand, automatic manufacturing systems include a complex network of manufacturing processes, inspections, midrange storages and automatic transport systems. One of the important points in these systems is the ability to reduce or increase the output from the production line affected by the decrease or increase in customer demand. Therefore, Fazlollahtabar et al., (2010) provided a flexible job shop scheduling system in order to optimize the flow of materials. The considered flexibility includes various workstations and products in the system under examination.

AGVs are also used to handle materials. The objective function considered in this study optimizes the flow of material according to the fluctuations in demand and production equipment's features. Sanchez-Salmeron et al., (2010) presented a new system of automatic material transport machines for integrated manufacturing system. The main task of handling transportation system (empty / full) among different workstations has been in a manufacturing factory in order to integrate the manufacturing and assembly processes in a factory. In this study, the transport system includes conveyors and AGVs. Salehipour et al., (2011) proposed a new framework to determine the workstations in a bilateral AGV transportation system. The objective function considered in this study minimizes the flow of material; in other words, the total displacement carried out by AGVs in a department of manufacturing system. Another decision taken in this study is allocation of workstations to AGVs. These researchers also proposed a heuristic algorithm to solve the provided mathematical model.

Production scheduling and routing: Lacomme et al., (2000) offered an optimization framework including a branch and bound algorithm and simulation in order to model a job shop model in which material transportation is done via an AGV. In this study, several laws have been considered to distribute AGVs among manufacturing facilities. Blazewicz et al., (1994) provided a bilateral algorithm for scheduling and routing in a flexible manufacturing system acting separately from each. Using a dynamic programming, they also reviewed whether an AGV suffices to do all movements during the planning horizon. They also offered a new method in order to avoid AGVs' interference. El Khayat et al., (2006) considered a production job shop system. They used the shortest route to displace material transport system between two machines. In this study, a mathematical model was developed for the problem. Dogan and Grossmann (2006) used Benders decomposition method to solve the simultaneity of production planning and scheduling AGVs in a flexible manufacturing system. It should be mentioned that the proposed method is as two levels.

Hamana et al., (2007) studied a job shop problem where part displacements were conducted by AGVs. It is assumed in this case that the sequence of operations has been already known. The guided routes of AGVs has been specific on the network of routs and points on which where that AGVs should stop are given to picked up and deliver. In this study, two restrictions are intended to prevent the lack of interference of AGVs. The first constraint says that two AGVs cannot be in a point in a moment of time and the second one says that none of AGVs cannot be in a rout in a moment of time. They used a cut algorithm to solve the examined problem for converting it into a major problem and sub- problem in a way that production scheduling and allocation of AGVs are solved in the main problem and routing in sub- problem.

Nishi et al., (2011) offered a decomposition algorithm for solving two-level scheduling and routing offered no interference. The study objective function intended to minimize the total weight of the work of the payment delays. So that a mixed-integer programming model was divided into two levels: high-level was related to the allocation of activities and their scheduling, while low level was related to the routing problem. The main problem was solved using Lagrange release technique and a lower bound was obtained for the value of the objective function. Then by considering two cuts and using analysis, they tried to close the answer to the initial problem as a lower bound and the answer to the Duval problem as the upper bound. Jawahar et al., (1998) conducted a study in order to create a logical connection between AGV activities and manufacturing scheduling. They also suggested a heuristic algorithm to implement the rules in order to avoid interference which the AGV distribution. The rules consist of the shortest time operation, the maximum operation time, the greatest time of the transfer and the shortest transit time. Evaluation criteria rules considered by comparing the time to do all the work were done.

Mahmoodi et al., (1999) examined the effects of timing and routing flexible rules on the operation of a flexible manufacturing system. In this study, they concluded that timing is highly dependent on the type of routing. Tanaka et al., (2010) studied the application of Petri Nets analysis approach to the optimization of distribution and routing without interfering AGV in a dynamic environment. In this study, the objective function is intended to minimize the movement AGV during the planning horizon. Ulusoy et al., (1997) investigated a problem of manufacturing scheduling and routing AGVs and used a genetic algorithm to solve it. Jerald et al., (2006) investigated scheduling of manufacturing machines on different parts with AGVs simultaneously. For this purpose, they adopted a specific manufacturing system and adapted non-traditional optimization technique called genetic algorithm. In this study, the objective function is intended to minimize the duration of unemployment of machines. They also have to show the quality of the solution method on a large scale compared with genetic algorithm.

Chaudhry et al., (2011) proposed a genetic algorithm to solve the problem of manufacturing scheduling and AGV simultaneously. In this study, the shortest route was used to allocate AGVs to machines. The proposed algorithm has been compared with four algorithms available in the literature. Nageswararao et al., (2012) proposed an optimization algorithm to solve the scheduling problem simultaneous with AGVs. The intended objectives of this study are to minimize time and minimize delays work completed. The proposed algorithm was evaluated for four different configurations and ten sets of jobs. Udhayakumar and Kumanan (2010) conducted a study to obtain a near-optimal solution to the problem of Job Shop Scheduling including two AGVs. The intended purpose of this study was to balance workload and minimize the duration of travels. They also used ant algorithm to solve the model.

Saidi-Mehrabad et al., (2015) studied Job Shop Scheduling with the routing information without the interference of AGVs and developed a mathematical model of mixed integer. In order to solve the proposed model, they used ant algorithm. Hamzeei et al., (2013) proposed a mixed-integer programming model to locate stations of shipment and delivery of two-way routs for an AGV system. They also used a simulated annealing algorithm to solve the proposed model. Fazlollahtabar et al., (2015) investigated Job Shop Scheduling with AGV scheduling by considering the time constraints of the delivery of orders to customers so that the intended purpose was to minimize the earliness and tardiness in the system. They also developed a heuristic algorithm to solve the model.

3. Statement of the Problem and Mathematical Model

The intended manufacturing system is an environment of a flow shop. There are a number of works in a storage on which a variety of manufacturing processes should be carried out by different machines. Since such works require one or more machines, manufacturing routes for them can be distinguished relative to each other. In addition, all AGVs start their activities over the planning horizon from the beginning of their primary storage as a starting point. It should be noted that at any point in time, only one task can be assigned to each AGV. Then, AGVs transfer works at the starting point i.e. the storage to delivery points located at manufacturing sites. Meanwhile, these transfers are carried out in a network of routes. AGVs remain waiting after they transfer the job to the first machine so that manufacturing process on the work would be completed and if necessary; transfer the job to other machines with regard to the manufacturing sequence. Otherwise, they are transmitted to the endpoint i.e. the storage. In addition, in the problem examined in this study, after the allocation of a job to AGV, the AGV can no longer be allocated to another job until the referred AGV finishes work assigned to the completed production activities required delivering the endpoints. Clearly, the AGV should not interfere with each other during transfer operations. In addition to the explanations provided above, other assumptions considered in this study are as follows:

- AGV capacity to move things is not limited.
- Failure during operation does not happen for machines and AGVs.
- Manufacturing machines are identical.
- The time to handle the tasks by AGVs is not negligible.
- AGV handling time depends on the type of job.
- Manufacturing process cannot be stopped within the process
- No machine can process more than one job at a moment of time. Parameters and indices n: The number of jobs in warehouse

m: The number of machines

(R, S): The number of position of machine on the network

k_q: The number of AGVs between machines q and q'

H: The number of period

j: The job index $j \in \{1, 2, \cdots, n\}$

q: The machine index $q \in \{1, 2, \cdots, m\}$

(r, s): The position of machine index on the network $r \in \{1, 2, \cdots, R\}$ and $s \in \{1, 2, \cdots, S\}$

l: The AGV index $l \in \{1, 2, \cdots, k_q\}$

t: The period index $t \in \{0, 1, 2, \cdots H\}$

k: The index of position which denotes to the job occupying the th position of the job sequence on the first machine $k \in \{1, 2, \cdots, n\}$

h: The index of position which denotes to the job assigned the th position of a job sequence on an AGV $h \in \{1, 2, \cdots, n\}$

$O_{jq(r,s)}$: The operation of job j on machine in point (r, s)

$\tilde{P}_{jq(r,s)}$: The fuzzy processing time of operation $O_{jq(r,s)}$

$T_{jq(r,s)}$: The transportation time required to move job j from machine q in point (r, s) to machine $q^{'}$ in point $(r^{'}, s^{'})$

$Tb_{(q(r,s)}$: The void moving time of an AGV from machine $q^{'}$ in point $(r^{'}, s^{'})$ to machine q in point (r, s)

$\tilde{d}_{kq}$: Fuzzy due date of job in the kth position of the sequence on machine q

$$b_{jq(r,s)} = \begin{cases} 1 & \text{If machine } q \text{ in point } (r,s) \text{ is a P/D point for job } j \\ 0 & \text{otherwise} \end{cases}$$

$$w_{jq(r,s)}(r^{'}, s^{'}) = \begin{cases} 1 & \text{If machine } q \text{ in point } (r,s) \text{ precedes machine } q^{'} \text{ in point} \\ & (r^{'}, s^{'}) \text{ for job } j \\ 0 & \text{otherwise} \end{cases}$$

$a_{jq(r,s)}$: The sequence of the machine q in P/D point (r,s) for job j

(a,b): Starting point where AGVs receive jobs from automatic warehouse

$(a^{'},b^{'})$: Ending point where AGVs deliver jobs to automatic warehouse

M: A big number

$$b_{jq(r,s)} = \begin{cases} 1 & \text{If machine } q \text{ in point } (r,s) \text{ is a P/D point for job } j \\ 0 & \text{otherwise} \end{cases}$$

$$w_{jq(r,s)}(r^{'},s^{'}) = \begin{cases} 1 & \text{If machine } q \text{ in point } (r,s) \text{ precedes machine } q^{'} \\ & \text{in point } (r^{'},s^{'}) \text{ for job } j \\ 0 & \text{otherwise} \end{cases}$$

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$(a^{'},b^{'})$: Ending point where AGVs deliver jobs to automatic warehouse

M: A big number

Variables

$$X_{jkt} \begin{cases} 1 & \text{If job } j \text{ occupies the } k\text{th position of the job sequence on the machines in time } t \\ 0 & \textit{otherwise} \end{cases}$$

$$Y_{jhlqt} \begin{cases} 1 & \text{If job } j \text{ occupies the hth position of the job sequence on AGV l that} \\ & \text{moves between machine } q \text{ and machine } q^{'} \text{ in time } t \\ 0 & \text{otherwise} \end{cases}$$

$$Z_{jhlq(r,s)t} \begin{cases} 1 & \text{If job } j \text{ occupies the hth position of the job sequence on AGV} \\ & \text{l that moves between machine } q \text{ in ponit } (r,s) \text{ and machine } q^{'} \\ & \text{in point } (r^{'},s^{'}) \text{ in time} t \\ 0 & \text{otherwise} \end{cases}$$

C_{kqt}: The completion time for processing the job in the kth position of the sequence on machine q

CT_{hlqt}: The completion time for transporting the job assigned to the hth position of the sequence on AGV l from machine q to machine $q^{'}$

$C_{\max}$: Maximum completion time

$\sum T_{kqt}$: The total tardiness, $\sum T_{kqt} = \sum_t \sum_k \sum_q \max\{0, C_{kqt} - \tilde{d}_{kqt}\}$

In addition, the following restrictions must always be met in order to produce the

$$w_{jq(r,s)}(r^{'},s^{'}) + w_{jq^{'}(r^{'},s^{'})(r,s)} = b_{jq(r,s)} \times b_{jq^{'}(r^{'},s^{'})} \quad \forall r,s,r^{'},s^{'},j,q,q^{'} \tag{1}$$

$$b_{jq(r,s)} \times a_{jq^{'}(r^{'},s^{'})} - b_{jq^{'}(r^{'},s^{'})} \times a_{jq(r,s)} \leq M w_{jq(r,s)(r^{'},s^{'})} \quad \forall r,s,r^{'},s^{'},j,q,q^{'} \tag{2}$$

$$b_{jq(r,s)} \times a_{jq^{'}(r^{'},s^{'})} - b_{jq^{'}(r^{'},s^{'})} \times a_j q(r,s) \geq -M w_{jq^{'}(r^{'},s^{'})(r,s)} \quad \forall r,s,r^{'},s^{'},j,q,q^{'} \tag{3}$$

Model

$$\min Z_1 = C_{\max} \tag{4}$$

$$\min Z_2 = \sum_t \sum_k \sum_q \max\{0, C_{kqt} - \tilde{d}_{kqt}\} \tag{5}$$

$$\sum_{k=1}^{n} X_{jkt} = 1, \quad \forall j, t \tag{6}$$

$$\sum_{j=1}^{n} X_{jkt} = 1, \quad \forall k, t \tag{7}$$

$$\sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Y_{jhlqt} = 1 \forall q, j(\tag{8}$$

$$\sum_{j=1}^{n} Y_{jhlq0} = 1, \quad \forall l, q, h \tag{9}$$

$$\sum_{j=1}^{n} Y_{jhlqt} \le 1, \quad \forall l, q, h, \quad \forall t \ge 1 \tag{10}$$

$$\sum_{w=1}^{h-1} Y_{jwlqt} \ge (h-1) Y_{jhlqt}, \forall l, q, j, t, \forall h > 1 \tag{11}$$

$$\sum_{w=h+1}^{n} Y_{jwlqt} \le (n-h) Y_{jhlqt}, \quad \forall l, q, j, t, \forall h < n \tag{12}$$

$$\sum_{h=1}^{n} Y_{jhlqt} \le \sum_{h=1}^{n} Z_{jhlq(a,b)t}, \quad \forall j, l, q, t \tag{13}$$

$$\sum_{h=1}^{n} Y_{jhlqt} \le \sum_{j' \in n,\, j' \ne j} \sum_{h=1}^{n} Z_{j'hlq(a',b'\,t-1}, \quad \forall j, l, q, t \tag{14}$$

$$\sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Z_{jhlq(r,s)t} \ge b_{jq(r,s)}, \quad \forall q, r, s, j \tag{15}$$

$$\sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Z_{jhlq(r,s)t} \le \sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Z_{jhlq'(r',s')t} + M\left(1 - w_{jq(r,s)(r',s')}\right), \quad \forall q, r, s, r^{'}, s^{'}, j \tag{16}$$

$$\sum_{l=1}^{k_q} \sum_{j=1}^{n} Z_{jhlq(r,s)t} \le 1, \quad \forall (r,s) - (a,b), t, h, q \tag{17}$$

$$Z_{jhlq(r,s-1)t+1} + Z_{j'wl'q(r,s)t+1} \le 3 - \left(Z_{jhlq(r,s)t} + Z_{j'wl'q(r,s-1)t)}\right) \quad \forall (r,s), l, l^{'}, h, w, j, j^{'}; l \ne l^{'}, j \ne j^{'} \tag{18}$$

$$Z_{jhlq(r-1,s)t+1} + Z_{j'wl'q(r,s)t+1} \leq 3 - \left(Z_{jhlq(r,s)t} + Z_{j'wl'q(r-1,s)t}\right),$$
$$\forall (r,s), l, l^{'}, h, w, j, j^{'};\ l \neq l^{'},\ j \neq j^{'} \tag{19}$$

$$\sum_{h=1}^{n}\sum_{q=1}^{m}\sum_{r=1}^{R}\sum_{s=1}^{S} Z_{jhlq(r,s)t}, \leq 1 \quad \forall l, j, t \tag{20}$$

$$Z_{jhlq(r,s)t} \leq Z_{jhlq(r+1,s)t+1} + Z_{jhlq(r-1,s)t+1} + Z_{jhlq(r,s+1)t+1} + Z_{jhlq(r,s-1)t+1} + Z_{jhlq(r,s)t+1} + MY_{jhlqt}, \quad \forall (r,s), t, q, h, l, j \tag{21}$$

$$C_{kqt} - \sum_{j=1}^{n} \tilde{d}_{jq(r,s)} X_{jkt} \geq C_{kq-1t} + \sum_{j=1}^{n} T_{jq(r,s)} X_{jkt}, \quad \forall q, k, t, (r,s) \tag{22}$$

$$C_{kqt} - \sum_{j=1}^{n} \tilde{P}_{jq(r,s)} X_{jkt} \geq C_{k-1qt}, \quad \forall k > 1, q, (r,s), t \tag{23}$$

$$C_{kq+1t} - \sum_{j=1}^{n} \tilde{P}_{jq+1(r,s)} X_{jkt} \geq \sum_{h=2}^{n}\sum_{l=1}^{k_q}\sum_{j=1}^{n} CT_{h-1lqt} X_{jkt} Y_{jhlqt} + \sum_{j=1}^{n} T_{jq(r,s)} X_{jkt}, \quad \forall q, t, k, (r,s) \tag{24}$$

$$CT_{hlqt} - \sum_{j=1}^{n} \left(Tb_{q(r,s)} + T_{jq(r,s)}\right) Y_{jhlqt} \geq CT_{h-1lqt}, \quad \forall h > 1, l, q, (r,s) \tag{25}$$

$$CT_{hlqt} - \sum_{j=1}^{n} \left(Tb_{q(r,s)} + T_{jq(r,s)}\right) Y_{jhlqt} \geq \sum_{k=1}^{n}\sum_{j=1}^{n} C_{kqt} X_{jkt} Y_{jhlqt}, \quad \forall l, q, h, t, (r,s) \tag{26}$$

$$C_{max} \geq C_{n,m,T} \tag{27}$$

$$X_{jkt}, Y_{jhlqt}, Z_{jhlq(r,s)t} \in 0, 1, \quad \forall j, k, q, l, t, (r,s) \tag{28}$$

$$C_{kqt}, CT_{hlqt}, C_{max} T_{kqt} \geq 0, \quad \forall k, q, l, t \tag{29}$$

The objective function (4) minimizes the maximum time to do all the jobs. The objective function (5) minimizes the total time delay in the manufacturing process of the delivery date specified by customers. Constraint (6) ensures that in each period, each job exactly occupies one position of the sequence of job on the machine. Limitation (7) ensures that each position can be occupied only once. Restrictions (8) to (12) are related to the allocation of jobs to AGVs. Restriction (8) ensures that each job occupies exactly and only one position of the sequence on the AGV. Restriction (9) states that each AGV should get one job in the time 0. Restriction (10) ensures that any position on any of the AGV must be occupied by atmost one job. Constraints (11) and (12) guarantee that the positions are assigned based on sequence. Constraint (13) ensures that one job is allocated to one AGV when the AGV is at the starting point. Constraint (14) states that when a new job can be assigned to an AGV that a job in the same instant of time is delivered to automatic storage by AGV. Constraint (15) states that any point of p / d required for the job j must be met by an AGV. Constraint (16) ensures that if the point (r, s) for job j is a prerequisite for $(r^{'}, s^{'})$, entering the AGV to that point is done earlier. Constraint (17) states that in a moment of time in any location other than the starting point a maximum of one AGV can exist. Constraints (18) and (19) ensure that AGVs have no interference with each other in neither vertical nor horizontal directions. Restriction (20) states that every AGV can be responsible for a maximum of handling one problem. Restriction (21) states that an AGV on any location can move in four adjacent directions or stay in the same place. Restrictions (22) to (24) are to calculate the time the job is completed. Constraints (25) and (26) are to calculate the time the job is completed. By AGVs Limitation (27) calculates the time taken to complete all the tasks. Restrictions (28) and (29) state the restrictions associated with decision variables.

4. **Solution Approaches**

4.1. **Uncertainty Approach.** With respect to the above mentioned consideration, a mixed integer programming model with fuzzy parameters is proposed. As indicated in previous sections, since the developed model pertains to the possibilistic programming category, an appropriate possibility distribution is considered for each parameter. Among those for proposed membership distribution function, triangular membership function is employed. This choice has been made because triangular membership functions are easily implemented and they are flexible in applying to various real-world problems [32]. Hence, we are benefiting from triangular membership functions in this study. Subsequently, a mixed integer programming model subject to fuzzy parameters is proposed for the problem of routing and scheduling of AGVS in flexible manufacturing system. Next, the proposed model, by virtue of a new technique based on possibilistic method [44, 28, 42], is converted to its commensurate deterministic version. For more details on general possibilistic nonlinear programming, interested readers may consult [33].

The commensurate adjuvant crisp model:

Suppose that $\tilde{c}$ is a triangular fuzzy number (TFN), the equation (30) as the membership function of $\tilde{c}$:

$$\mu_{\tilde{c}}(x) = \begin{cases} f_{c(x)} = \dfrac{x - c^p}{c^m - c^p} & \text{if} \quad c^p \leq x \leq c^m \\ 1 & \text{if} \quad x = c^m \\ g_{c(x)} = \dfrac{c^o - x}{c^o - c^m} & \text{if} \quad c^m \leq x \leq c^o \\ 0 & \text{if} \quad x \leq c^p \; or \; x \geq c^o \end{cases} \tag{30}$$

The following FMP model is considered, in which all parameters are defined as TFNs:

$$\begin{aligned}
&\min z = \tilde{c}^t x \\
&s.t. \\
&\quad \tilde{a}_i x \geq \tilde{b}_i, i = 1, \ldots, l \\
&\quad \tilde{a}_i x \geq \tilde{b}_i, i = l+1, \ldots, m \\
&\quad x \geq 0
\end{aligned} \tag{31}$$

The commensurate crisp α-parametric model of the model (31) is able to be written as bellows [28]:

$$\begin{aligned}
&\min z = EV(\tilde{c})x \\
&s.t. \\
&\quad [(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}, \qquad i = 1, 2, \ldots, l \\
&\quad \left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i} + \frac{\alpha}{2}E_1^{a_i}\right]x \geq \frac{\alpha}{2}E_2^{b_i} + \left(1-\frac{\alpha}{2}\right)E_1^{b_i}, \quad i = l+1, \ldots, m \\
&\quad \left[\frac{\alpha}{2}E_2^{a_i} + \left(1-\frac{\alpha}{2}\right)E_1^{a_i}\right]x \leq \left(1-\frac{\alpha}{2}\right)E_1^{b_i} + \frac{\alpha}{2}E_1^{b_i}, \quad i = l+1, \ldots, m \\
&\quad x \geq 0.
\end{aligned} \tag{32}$$

Where

$$EV(\tilde{c}) = \frac{c^p + 2c^m + c^o}{4}, \quad E_1^a = \frac{1}{2}(a^p + a^m),$$
$$E_2^a = \frac{1}{2}(a^m + a^o), \quad E_1^b = \frac{1}{2}(b^p + b^m) and E_2^b = \frac{1}{2}(b^m + b^o).$$

For details on the method, the reader can refer to [44]. Based on the above explanations, the commensurate adjuvant crisp model of the proposed model is as bellows:

Model

$$\min Z_1 = C_{\max} \tag{33}$$

$$\min Z_2 = \sum_t \sum_k \sum_q \max\left\{0, C_{kqt} - \left(\frac{d_{kqt}^p + 2d_{kqt}^m + d_{kqt}^o}{4}\right)\right\} \tag{34}$$

$$\sum_{k=1}^{n} X_{jkt} = 1, \quad \forall j, t \tag{35}$$

$$\sum_{j=1}^{n} X_{jkt} = 1, \quad \forall k, t \tag{36}$$

$$\sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Y_{jhlqt} = 1, \quad \forall q, j \tag{37}$$

$$\sum_{j=1}^{n} Y_{jhlq0} = 1, \quad \forall l, q, h \tag{38}$$

$$\sum_{j=1}^{n} Y_{jhlqt} \leq 1, \quad \forall l, q, h, \quad \forall t \geq 1 \tag{39}$$

$$\sum_{w=1}^{h-1} Y_{jwlqt} \geq (h-1) Y_{jhlqt}, \quad \forall l, q, j, t, \quad \forall h > 1 \tag{40}$$

$$\sum_{w=h+1}^{n} Y_{jwlqt} \leq (n-h) Y_{jhlqt}, \quad \forall l, q, j, t, \quad \forall h < n \tag{41}$$

$$\sum_{h=1}^{n} Y_{jhlqt} \leq \sum_{h=1}^{n} Z_{jhlq(a,b)t}, \quad \forall j, l, q, t \tag{42}$$

$$\sum_{h=1}^{n} Y_{jhlqt} \leq \sum_{j' \in n,\, j' \neq j} \sum_{h=1}^{n} Z_{j'hlq(a',b')t-1}, \quad \forall j, l, q, t \tag{43}$$

$$\sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Z_{jhlq(r,s)t} \geq b_{jq(r,s)}, \quad \forall q, r, s, j \tag{44}$$

$$\sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Z_{jhlq(r,s)t} \leq \sum_{t=0}^{H} \sum_{l=1}^{k_q} \sum_{h=1}^{n} Z'_{jhlq}(r', s')t + M\left(1 - w_{jq(r,s)(r',s')}\right), \quad \forall q, r, s, r', s', j \tag{45}$$

$$\sum_{l=1}^{k_q} \sum_{j=1}^{n} Z_{jhlq(r,s)t} \leq 1, \quad \forall (r,s) - (a,b), t, h, q \tag{46}$$

$$Z_{jhlq(r,s-1)t+1} + Z_{j'wl'q(r,s)t+1} \leq 3 - \left(Z_{jhlq(r,s)t} + Z_{j'wl'q(r,s-1)t}\right) \quad \forall (r,s), l, l', h, w, j, j'; l \neq l', j \neq j' \tag{47}$$

$$Z_{jhlq(r-1,s)t+1} + Z_{j'wl'q(r,s)t+1} 3 - \left(Z_{jhlq(r,s)t} + Z_{j'wl'q(r-1,s)t}\right) \quad \forall (r,s), l, l', h, w, j, j'; l \neq l', j \neq j' \tag{48}$$

$$\sum_{h=1}^{n} \sum_{q=1}^{m} \sum_{r=1}^{R} \sum_{s=1}^{S} Z_{jhlq(r,s)t} \leq 1, \quad \forall l, j, t \tag{49}$$

$$Z_{jhlq(r,s)t} \leq Z_{jhlq(r+1,s)t+1} + Z_{jhlq(r-1,s)t+1} + Z_{jhlq(r,s+1)t+1} + Z_{(jhlq(r,s-1)t+1} + Z_{jhlq(r,s)t+1} + MY_{jhlqt}, \quad \forall (r,s), t, q, h, l, j \tag{50}$$

$$C_{kqt} - \sum_{j=1}^{n} \left[\left(1 - \frac{\alpha}{2}\right) \left(\frac{P^m_{jq(r,s)} + P^o_{jq(r,s)}}{2} \right) + \frac{\alpha}{2} \left(\frac{P^p_{jq(r,s)} + P^m_{jq(r,s)}}{2} \right) \right] X_{jkt} \geq C_{kq-1t} + \sum_{j=1}^{n} T_{jq(r,s)} X_{jkt}, \quad \forall q, k, t, (r,s) \tag{51}$$

$$C_{kqt} - \sum_{j=1}^{n} \left[\left(1 - \frac{\alpha}{2}\right) \left(\frac{P^m_{jq(r,s)} + P^o_{jq(r,s)}}{2} \right) + \frac{\alpha}{2} \left(\frac{P^p_{jq(r,s)} + P^m_{jq(r,s)}}{2} \right) \right] X_{jkt} \geq C_{kq-1t} \quad \forall k > 1, q, (r,s), t \tag{52}$$

$$C_{kqt} - \sum_{j=1}^{n} \left[\left(1 - \frac{\alpha}{2}\right) \left(\frac{P^m_{jq(r,s)} + P^o_{jq(r,s)}}{2} \right) + \frac{\alpha}{2} \left(\frac{P^p_{jq(r,s)} + P^m_{jq(r,s)}}{2} \right) \right] X_{jkt} \geq \sum_{h=2}^{n} \sum_{l=1}^{k_q} \sum_{j=1}^{n} CT_{h-1lqt} X_{jkt} Y_{jhlqt} + \sum_{j=1}^{n} T_{jq(r,s)} X_{jkt}, \quad \forall q, t, k, (r,s) \tag{53}$$

$$CT_{hlqt} - \sum_{j=1}^{n} \left(Tb_{q(r,s)} + T_{jq(r,s)} \right) Y_{jhlqt} \geq CT_{h-1lqt}, \quad \forall h > 1, l, q, (r,s) \tag{54}$$

$$CT_{hlqt} - \sum_{j=1}^{n} \left(Tb_{q(r,s)} + T_{jq(r,s)} \right) Y_{jhlqt} \geq \sum_{k=1}^{n} \sum_{j=1}^{n} C_{kqt} X_{jkt} Y_{jhlqt}, \quad \forall l, q, h, t, (r,s) \tag{55}$$

$$C_{\max} \geq C_{n,m,T} \tag{56}$$

$$X_{jkt}, Y_{jhlqt}, Z_{jhlq(r,s)t} \in \{0,1\}, \quad \forall j, k, q, l, t, (r,s) \tag{57}$$

$$C_{kqt}, CT_{hlqt}, C_{\max} T_{kqt} \geq 0, \quad \forall k, q, l, t \tag{58}$$

4.2. **Meta-heuristic Algorithm.** In most of optimization problems, there are different objective functions which are in conflict. Therefore, an ideal solution which optimizes all the objective functions simultaneously cannot be found. In these cases, Pareto optimal solutions can be found for the problem. Multi-objective meta-heuristic algorithms are one of the most commonly used methods to obtain Pareto optimal solutions for a multi-objective optimization problem. In this paper, two multi-objective meta-heuristic algorithms named Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and multi-objective particle swarm optimization (MOPSO) are used to solve the problem.

4.2.1. *NSGA-II.* One of the most efficient and well-known optimization algorithms based on Pareto solutions provided by Deb et al., (2001) known as Non-dominated Sorting Genetic Algorithm-II (NSGA-II). In solving multi-objective problems, we cannot consider a separate optimal solution as single objective problem. Therefore, we concern with a set of solutions known as non-dominated solutions. Of the finite set of solutions, answers will be the right solution acceptable performance to all have goals. Solving the multi-objective problems with Pareto approach are among the complex problems that often give no special optimal solution for these methods. In this method, as a population of solutions is searched, basically, in every implementation of algorithm, Pareto optimal solutions can be found. In NSGA-II, two important criteria of non-dominated ranking and crowding distance were used. In the first criterion, ranking is performed based on the concept of dominance. For non-dominated ranking of population, firstly, each solution is compared with other solutions so that it is determined that if it is dominant or non-dominant. A set of solutions that none of them is dominance or non-dominant are created that these solutions is the first front of non-dominant fronts. To determine the next fronts, solutions available in the first front are ignored. Then, this is repeated with dominant concept. This process continues up to fronting all non-dominance solutions. In the second criterion, crowding distance is used in the way that to measure the density of solution around the certain solution in the available population, the average distance of this solution from both solutions near it is calculated based on objective function. As its value is higher, it will be better. In this algorithm, the number of children population (Q_t) is made using the parental population pt. Then the two populations are integrated so that population R_t is created. Then, using non-dominance concept, non-dominance sorting is used to cluster all population R_t. By one comparison using prioritizing, the next population is filled with these priorities. Since all members R_t may cannot be included in P_{t+1}, crowding distance concept is used to fill the population in a way that solutions that are in the lower crowding area are prioritized to fill the P_{t+1} and population P_{t+1} is created. The evolution of NSGA-II algorithm is shown in Figure 1.

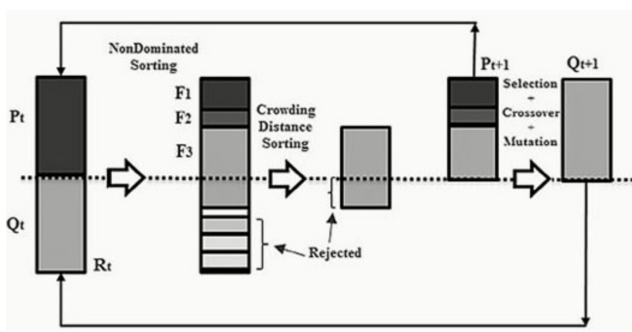

FIGURE 1. The Evolution of the NSGA-II (Source: Hoseini Rahdar 2016)

NSGA-II Operators

To find high-quality solutions and producing the new solution from old solutions in NSGA-II algorithm, mutation and crossover operators are used. For the production of new child in each iteration of the algorithm, single-point crossover operator has been implemented. This operator is the most common form to produce two children from two parent chromosomes with a cut. For this purpose, a point in the chromosome selected randomly and it is cut. After determining the position of crossover, each of the two parents is divided into two parts and the exchange is done in the way that one part of the first parent is integrated with remaining part of the second parent, resulting in creation of two new solutions. Figure 2 shows the implementation of crossover operator used.

0	1	0	0	1	1
1	1	0	1	0	0

0	1	**0**	**0**	**1**	**1**
1	1	**0**	**1**	**0**	**0**

Figure 2. Implementation of Crossover Operator

The mutation operator ensures that the genetic algorithm will achieve to optimal solution or solution close to it. With applying this operator, neighborhood search is conducted and search space is developed to achieve to absolute optimum. The used mutation operator is swap and inversion type. In the swap type, two points are selected randomly and their position is displaced with each other, while in the inversion, each number is displaced randomly in the length of chromosome chain. Mutation operator used for problem in inversion.

4.2.2. *MOPSO.* A multi-objective particle swarm optimization algorithm (MOPSO) was presented for the first time by Coello in (2004). The approach of this algorithm is based on the concept of Pareto solutions to estimate the flight route of each particle and maintaining the previous non-dominance solutions found in the one reservoir so that these solutions are used by other particles. The velocity of each particle is calculated using equation (59).

$$vel[i] = w.vel[i] + c_1 r_1 (pbest[i] - pop[i]) + c_2 r_2 (REP[h] - pop[i]) \tag{59}$$

Pbest $[i]$ is the best place i^{th} particle has found it so far. REP $[h]$ is the amount that is taken from the reservoir. The position of each particle is updated by equation (60) by adding velocity obtained from equation (59).

$$pop[i] = pop[i] + vel[i] \tag{60}$$

When the current position of particle is better than the position of its memory, the position of the particle emerges using the equation (61):

$$pbest[i] = pop[i] \tag{61}$$

Using the concept of dominance, if the current position be dominated by a position in the memory the position is preserved in memory, otherwise, this position is replaced by the position of the memory and if none of them is not dominated by another one, one of them is selected randomly.

4.3. **Parameter Setting.** In order to improve the performance of proposed algorithms, it is necessary that input parameters of algorithms be set. There are various methods for parameter setting. Taguchi method is one of the most efficient methods of setting the parameters of algorithm. Taguchi (1987) proposed for the first time the parameter setting method to design the process that its objective was to minimizing the variations and sensitivity of disturbance factors. In a designing an efficient parameter is firstly identifying and setting the factors minimizing the variations of solution variable and identifying the controllable and non-controllable factors. The ultimate goal of this method is finding the optimal combination of controllable factors. S/N ratio is quality index shown in equation (62). The objective of Taguchi experiments is finding the best level of each factor. This condition occurs when the ratio of S/N related factor is maximized at that level.

$$S/N\ ratios = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{62}$$

Input parameters of the NSGA-II algorithm include initial population number (npop), the probability of crossover operator (pc), the probability of mutation (pm) and the number of iteration of algorithm (maxit) and MOPSO algorithm parameters include initial population number (npop), the number of algorithm iteration (maxit), $C1$ (Personal Learning Coefficient) and $C2$ (Global Learning Coefficient). Different levels of algorithm parameters are shown in Table 1. Using the concept

Algorithm	Parameter	Low(1)	Medium(2)	High(3)
NSGA-II	npop	50	70	90
	maxit	100	200	300
	P_m	0.1	0.2	0.4
	P_c	0.7	0.8	0.9
MOPSO	npop	50	60	70
	maxit	100	150	200
	C_1	1	1.5	2
	C_2	1	1.5	2

Table 1. The Parameters of the Algorithms and Their Levels

of experiments design and given the number of factors of algorithms, orthogonal arrays (L9) is created. To evaluate the proposed algorithms multiple criteria are used. In this article, the number of solutions of Pareto (nos), the largest diversity, spacing, and the distance of ideal solution (MID) and solution time (Time) have been used. To determine the best answer, each experiment was iterated 5 times and in each iteration,5 criteria were measured that Table 2 shows matrix obtained by 9 performed experiment for NSGA-II algorithm. Table 3 shows normalized matrix and total criteria for one iteration. Total normalized values of criteria for 5iterations of algorithms presented are in Tables 4 and 5.

Figures 3 and 4 show index value of S/N for the algorithm NSGA-II and MOPSO. According to this index, the optimal values for the algorithms are presented in Table 6.

5. **Computational Results**

In order to evaluate the performance of proposed algorithms, we implemented experimental problems on various aspects and values of the five evaluation criteria for both algorithms are investigated. For this purpose, 30 problems in small, medium and large sizes were examined. The instances are constructed based on a benchmark set of test problems established by Taillard (1993). Moreover, the obtained results for each objective function ($\alpha = 0.5$) for 30 test problems are shown in Table 7. In addition, results of implementation of parameters NSGA-II and MOPSO are shown in Tables 8 and 9.

nos	diversity	spacing	MID	Time
153	5726.281567	0.781200295	1.000049308	221.6565133
217	7653.644465	0.911742369	1.000052042	633.1391645
239	8103.404104	0.812373809	1.000045434	1240.123389
143	6183.216395	0.858402681	1.000047916	410.0575038
262	8564.579086	0.851008113	1.000051053	1010.601764
243	8016.522309	0.881170205	1.000049408	1308.187981
218	7709.592639	0.887158092	1.000048358	642.8507801
270	9707.80481	0.918633369	1.000051089	1226.660557
215	8121.966495	0.932985152	1.000047031	1744.623397

Table 2. The Metrics Obtained by NSGA-II

nos	diversity	spacing	MID	Time	sum
0.566666667	0.5898637	1	0.9999961	1	4.156526
0.803703704	0.7884011	0.85682131	0.9999934	0.3500913	3.799011
0.885185185	0.8347308	0.96162664	1	0.1787375	3.86028
0.52962963	0.6369325	0.91006274	0.9999975	0.5405498	3.617172
0.97037037	0.8822364	0.91797044	0.9999944	0.2193312	3.989903
0.9	0.8257812	0.88654869	0.999996	0.1694378	3.781764
0.807407407	0.7941644	0.88056492	0.9999971	0.3448024	3.826936
1	1	0.85039399	0.9999943	0.1806991	4.031087
0.796296296	0.836643	0.83731268	0.9999984	0.1270512	3.597302

Table 3. Normalized Metrics Obtained by NSGA-II

npop	maxit	pm	pc	sum1	sum2	sum3	sum4	sum5	S/N
1	1	1	1	4.15653	4.14997	3.84998	3.66359	3.91519	11.8956
1	2	2	2	3.79901	3.39393	3.73309	3.44043	3.45899	11.0136
1	3	3	3	3.86028	3.6824	3.92002	3.91466	3.87392	11.7029
2	1	2	3	3.61717	3.82938	3.59999	3.51475	3.85355	11.3068
2	2	3	1	3.9899	4.04231	3.70755	3.65469	3.63961	11.5849
2	3	1	2	3.78176	3.20468	3.85377	3.50169	3.72852	11.1001
3	1	3	2	3.82694	3.68806	3.6972	3.5747	3.84939	11.4182
3	2	1	3	4.03109	3.76805	3.44484	3.39126	3.63482	11.2047
3	3	2	1	3.5973	4.05673	4.0175	3.45327	3.91054	11.5584

Table 4. Experimental Results of NSGA-II

npop	maxit	c1	c2	sum1	sum2	sum3	sum4	sum5	S/N
1	1	1	1	4.18986	4.21372	4.16692	4.17018	4.17097	12.4281
1	2	2	2	4.3462	4.29307	4.19098	4.15899	4.22749	12.5508
1	3	3	3	4.29581	4.20248	4.14174	4.21011	4.21843	12.4915
2	1	2	3	4.67806	4.67379	4.48034	4.52657	4.58181	13.2289
2	2	3	1	3.75448	3.97613	3.75066	3.88352	3.77263	11.6514
2	3	1	2	4.18492	4.25613	4.19629	4.04511	4.20869	12.416
3	1	3	2	4.51642	4.62089	4.36186	4.40582	4.49274	13.0194
3	2	1	3	4.3139	4.49647	4.32896	4.3197	4.48978	12.844
3	3	2	1	3.7872	4.0129	3.73229	3.68079	3.80609	11.5933

Table 5. Experimental Results of MOPSO

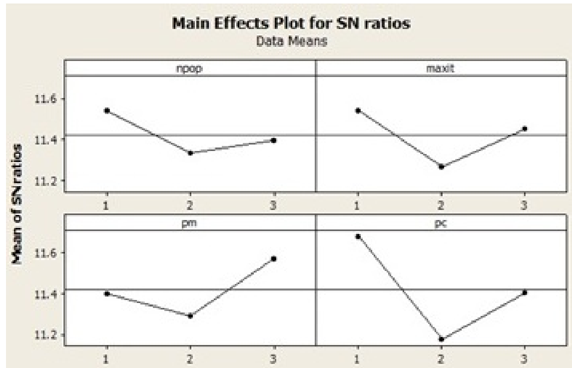

FIGURE 3. The Value of S/N Index for Parameters of Algorithm NSGA-II

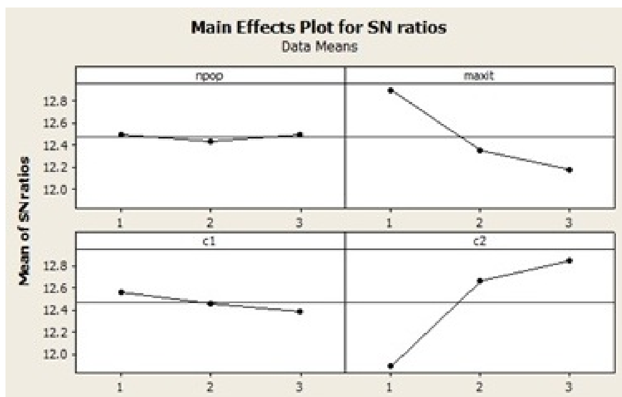

FIGURE 4. The Value of S/N Index for Parameters of the Algorithm MOPSO

NSGA-II	Optimal Value	MOPSO	Optimal Value
npop	50	npop	50
maxit	100	maxit	100
P_m	0.4	C_1	1
P_c	0.7	C_2	2

TABLE 6. Tuned Parameters for NSGA-II and MOPSO

Considering the production of Pareto solutions, we select the problem 2 as sample and examine a set of Pareto solutions and Pareto diagram for this problem. For NSGA-II algorithm the number of obtained solutions is 56 and 50 Pareto solutions were obtained for MOPSO algorithm that its results are shown in Table 10 and 11.

Test	NSGA-II		MOPSO	
NO	f_1	f_2	f_1	f_2
1	6.78336887	15.23552239	7.654469462	16.11410256
2	9.313477068	23.12821429	10.70111688	23.743
3	10.80340921	28.52981132	11.54785965	36.37068627
4	11.3582906	37.1565812	14.23474007	41.73561798
5	14.27119941	52.93931034	17.74965036	56.90043478
6	16.35464479	89.37360465	18.24336821	121.3234646
7	18.6656136	132.7169072	24.40121254	188.905
8	20.37064244	170.0714607	27.91216548	216.368254
9	23.11694444	201.3734146	28.90178229	262.4779861
10	26.61961849	221.559375	30.74777597	298.8932544
11	29.00158619	209.5310784	37.8432595	281.843961
12	33.72803465	385.9770297	40.9726833	500.3267516
13	40.04881581	451.4499038	45.21195608	648.5592386
14	39.49955738	420.8115447	48.00542041	615.0921557
15	40.21320562	434.1490426	47.61133569	583.4377654
16	42.81788776	473.446129	52.69587911	755.3466667
17	46.01310131	628.9708527	53.52544173	829.7426368
18	51.3223136	771.8427083	57.74025286	1115.747326
19	53.34162922	829.6401156	60.16836523	1145.583175
20	54.52298377	1018.455273	63.14511708	1291.241964
21	59.21758736	1035.964259	65.60212376	1338.073333
22	62.27492049	1189.349083	73.83600326	1592.299968
23	70.58650775	1446.619796	74.1439191	1905.966366
24	66.78918849	1624.876165	77.8774309	2093.074706
25	68.54750682	1481.055169	74.95165033	1873.195378
26	73.38175294	1778.141648	81.87606468	2376.710215
27	71.69462063	1768.566435	85.04640016	2316.137865
28	69.47143582	2030.236754	89.14597804	2841.024254
29	72.74927482	2237.012614	90.02546458	3120.485711
30	76.79255252	2576.774054	84.67746449	3220.800309

Table 7. Values of Objective Functions

Statistical comparison

To analyze the data for the indicators, the number of Pareto solutions (nos), the largest expansion of (diversity), spacing, the ideal answer (MID) and solution time (Time) Anova analysis used. In this analysis, according to a criterion of analysis of variance to compare used algorithms .The output of these analyses is shown in Tables 12-16 using minitabe16. The p-value in the results of single factor Anova for nos and diversity is less than 0.05. Therefore, we can infer that there are significant difference between the algorithms considering nos and diversity criteria. In addition, there are no significant differences between the two meta-heuristic algorithms in term of spacing, MID and Time criteria.

To select more efficient algorithm for proposed model, conclusion can be made according to boxplot diagrams. As it is better that criterion of the number of Pareto solutions and diversity to be greater, so it should have greater mean and variance. However, it is better that the criteria of spacing, distance form ideal solution to be lower. Therefore, they should have lower mean and variance. Boxplot diagrams for presented criteria are shown in Figures 5-9. As can be seen, the mean number of Pareto solutions and the greatest diversity are greater in the MOPSO algorithm.

Test problem	nos	diversity	NSGA-II spacing	MID	time
1	86	2090.53	0.97499	1.0001	33.6034
2	56	1261.75	0.88087	1.00019	23.5731
3	106	2477.98	0.83161	1.00013	51.2114
4	117	2712.91	0.82182	1.00012	46.0598
5	87	2882.88	1.09468	1.0001	35.3128
6	86	2842.7	0.74311	1.00007	49.0197
7	97	3375.77	0.92917	1.00006	51.51
8	89	3423.86	0.96094	1.00006	46.2199
9	82	2982.69	0.69326	1.00005	56.2052
10	112	4216.98	0.9915	1.00006	66.1218
11	102	4037.4	1.06001	1.00008	62.121
12	101	5061.28	0.95111	1.00005	74.0176
13	104	4300.52	0.94603	1.00006	94.0294
14	123	4579.31	0.72962	1.00007	99.8418
15	94	4894.46	0.98402	1.00006	85.612
16	93	4885.85	0.92387	1.00006	90.7809
17	129	6448.41	0.95634	1.00005	101.789
18	144	7177.25	0.85939	1.00004	144.735
19	173	7495.09	0.71712	1.00004	289.04
20	165	7869.84	0.75985	1.00004	301.133
21	162	8750.45	0.90595	1.00004	305.342
22	120	6657.71	0.78409	1.00004	313.175
23	196	10767.4	0.77723	1.00004	450.45
24	133	8350.3	0.86995	1.00003	394.155
25	178	9933.85	0.77373	1.00004	406.675
26	182	10139.4	0.84344	1.00003	469.33
27	230	11860.5	0.88892	1.00003	527.077
28	228	12704.9	0.83827	1.00003	639.585
29	241	12166.3	0.89682	1.00003	649.6
30	185	10690.6	0.92213	1.00003	634.073
Ave	133.37	6234.63	0.87699	1.000061	219.713

Table 8. Results of Criteria for Algorithm NSGA-II and MOPSO

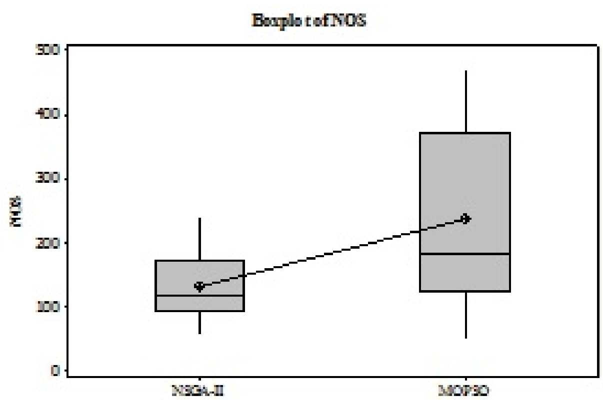

Figure 5. Boxplot Diagram of Nos Criterion

Test	MOPSO				
problem	nos	diversity	spacing	MID	time
1	78	1743.38	0.80054	1.00015	10.5272
2	50	1592.89	0.85316	1.00017	8.8600
3	102	2743.56	0.92628	1.00012	16.5001
4	89	2253.81	0.89637	1.00019	13.6213
5	115	3419.56	0.91883	1.00012	16.4344
6	127	3984.24	0.81373	1.00007	25.1795
7	122	4387.96	0.86861	1.00007	28.7071
8	126	4973.42	1.02314	1.00007	35.4825
9	144	6013.76	0.75677	1.00006	39.8129
10	169	6194.24	0.90837	1.00007	43.6126
11	154	6768.55	0.88345	1.00009	42.4253
12	157	7643.14	0.80691	1.00006	60.3998
13	197	9277.83	0.88337	1.00006	69.4253
14	167	8598.92	0.8737	1.00006	64.9786
15	179	9133.19	0.8167	1.00006	65.5478
16	177	9648.08	0.82331	1.00006	69.6912
17	201	10838.5	0.77549	1.00005	83.2749
18	187	12049	0.76734	1.00005	102.928
19	315	17557.9	0.80867	1.00004	311.809
20	331	19234	0.84688	1.00005	346.408
21	351	19345.7	0.78247	1.00005	333.141
22	315	20570.6	0.70545	1.00004	375.82
23	377	24941.2	0.85587	1.00004	452.582
24	374	25220.7	0.8417	1.00004	458.502
25	370	23932.1	0.85109	1.00004	427.716
26	372	25899.2	0.82795	1.00004	513.663
27	431	30047.1	0.85852	1.00004	546.29
28	456	31702.2	0.90375	1.00003	657.324
29	471	34249.9	0.84565	1.00003	688.875
30	453	38084.8	0.93527	1.00002	655.781
Ave	238.567	14068.3	0.84864	1.00007	218.844

Table 9. Results of Criteria for Algorithm NSGA-II and MOPSO

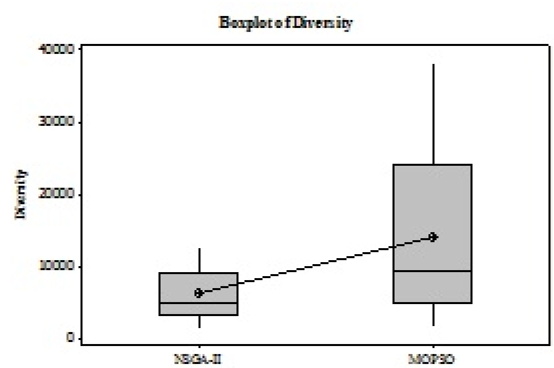

Figure 6. Boxplot Diagram of Diversity Criterion

Pareto solution	NSGA-II		MOPSO	
	f1	f2	f1	f2
1	6.8630137	17	7.5454545	18.8
2	7.6712329	18.1	7.3246753	20.45
3	10.630137	24.07	7.4545455	20.11
4	11.482759	24.93	6.2428571	13.01
5	7.2191781	16.89	7.9285714	22.78
6	10.655172	26.34	11.1	26.02
7	7.2191781	16.85	12.779221	27.22
8	10.287356	23.88	13.103896	27.42
9	6.6091954	16.71	8.4285714	19.7
10	7.6781609	18.82	10.428571	25.6
11	7.890411	19.25	10.657143	25.81
12	8.8630137	23.53	6.012987	16.47
13	13.45977	28.85	9.2285714	23.37
14	9.3424658	23.52	6.8441558	18.07
15	8.5172414	23.35	6.8441558	19.02
16	8.5172414	22.45	12.242857	27.06
17	10.689655	23.5	6.3636364	15.61
18	11.908046	28.43	13.685714	26.26
19	12.229885	28.68	15.614286	27.76
20	8.6438356	23.49	13.896104	26.53
21	10.60274	28.67	15.957143	27.8
22	9.816092	24.09	15.614286	27.65
23	10.136986	26.35	7.4428571	18.88
24	10.60274	28.63	11.311688	24.29
25	12.229885	28.76	10.961039	27.49
26	6.4252874	16.67	15.542857	27.02
27	12.671233	28.87	15.614286	27.78
28	12.873563	28.8	8.5142857	23.3
29	8.4597701	16.54	5.7012987	15.71
30	11.114943	28.18	13.012987	27.41
31	8.8630137	23.57	9.7532468	26.41
32	12.229885	26.62	15.614286	27.71
33	6.9863014	18.6	9.5324675	26.35
34	7.7586207	22.17	13.038961	27.41
35	7.6575342	19.49	15.957143	27.75
36	10.835616	27.2	10.363636	27.05
37	7.7816092	20.39	10.385714	23.48
38	6.6091954	16.95	12.542857	27.36
39	9.4712644	25.84	9.1	24.33
40	10.011494	24.77	7.012987	18.29
41	7.8965517	17.27	14.528571	26.91
42	9.8082192	22.62	14.103896	27.51
43	7.7808219	23.25	9.0519481	18.74
44	7.9425287	22.36	7.2337662	18.59
45	8.5172414	22.56	8.5142857	24.22
46	7.6781609	18.86	10.584416	27.07

Table 10. Sample Pareto Solutions for Problem 2

Pareto solution	NSGA-II		MOPSO	
	f1	f2	f1	f2
47	10.37931	24.13	11.987013	25.49
48	8.8767123	26.21	13.792208	27.42
49	10.150685	26.77	5.8311688	13
50	8.9770115	23.78	12.728571	27.66
51	7.7123288	19.85	···	···
52	9.3793103	23.93	···	···
53	9.4712644	26.84	···	···
54	9.4252874	24.03	···	···
55	10.83908	24.24	···	···
56	7.2054795	18.68	···	···

Table 11. Sample Pareto Solutions for Problem 2

Source	DF	SS	MS	F	P-Value
Factor	1	166006	166006	17.11	0.000
Error	58	562682	9701		
Total	59	728688			

Table 12. Analysis of Variance for Nos Criterion

Source	DF	SS	MS	F	P-Value
Factor	1	920497882	920497882	14.16	0.000
Error	58	3771200581	65020700		
Total	59	4691698463			

Table 13. Analysis of Variance for Diversity Criterion

Source	DF	SS	MS	F	P-Value
Factor	1	0.01206	0.01206	1.69	0.198
Error	58	0.41274	0.00712		
Total	59	0.42479			

Table 14. Analysis of Variance for Spacing Criterion

Source	DF	SS	MS	F	P-Value
Factor	1	0.0000000	0.0000000	0.44	0.509
Error	58	0.0000001	0.0000000		
Total	59	0.0000001			

Table 15. Analysis of Variance for MID Criterion

Source	DF	SS	MS	F	P-Value
Factor	1	11	11	0.00	0.988
Error	58	2847483	49095		
Total	59	2847494			

Table 16. Analysis of Variance for Time Criterion

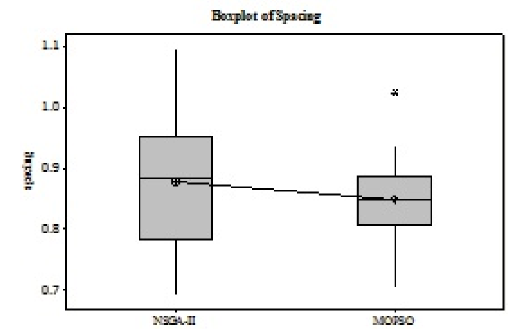

FIGURE 7. Boxplot Diagram of Spacing Criterion

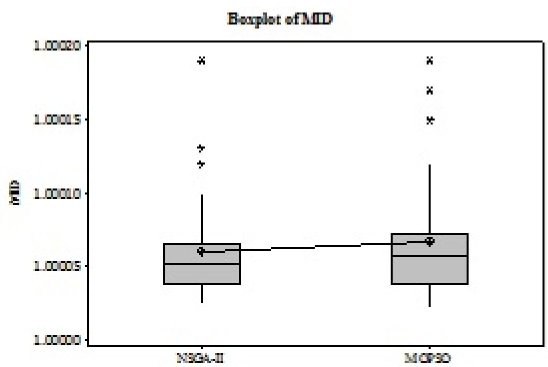

FIGURE 8. Boxplot Diagram of MID Criterion

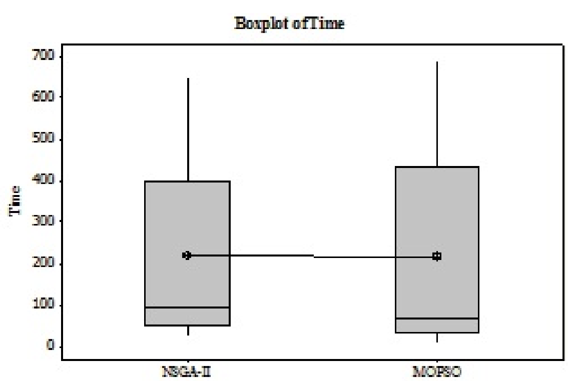

FIGURE 9. Boxplot Diagram of Time Criterion

6. Conclusion

In this paper, a bi-objective optimization model for integrating flow shop scheduling and routing AVGs in a flexible manufacturing system was developed. Therefore, in order to solve a realistic problem, foregoing parameters are considered as fuzzy in our proposed model. Subsequently, to solve fuzzy mathematical programming model, one of the most effective technique in the literature is used. To solve the problem studied, two meta-heuristic algorithms of Non-dominated Sorting Genetic Algorithm-II (NSGAII) and multi-objective particle swarm optimization (MOPSO) are offered that the accuracy of mathematical models and efficiency of algorithms provided are assessed through numerical examples.

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