

An Integrated Grey-Based Approach for Multi FMSs Combination Selection

Hasan HOSSEINI-NASAB¹, Maryam DEHGHANBAGHI²,
Jurgita ANTUCHEVICIENE^{3*}, Ehsan MEHRABANFAR⁴

¹*Department of Industrial Engineering, Yazd University, Iran*

²*Department of Industrial Engineering, Faculty of Engineering, Robat Karim Branch Islamic Azad University, Tehran, Iran*

³*Department of Construction Technology and Management Vilnius Gediminas Technical University, Lithuania*

⁴*Young Researchers and Elites Club, North Tehran Branch Islamic Azad University, Tehran, Iran*

e-mail: hhn@yazd.ac.ir; dehghanbaghi@yahoo.com; jurgita.antucheviciene@vgtu.lt; e.mehrabanfar@aut.ac.ir

Received: March 2016; accepted: August 2016

Abstract. In the fierce global competition, cost, quality and customer satisfaction appears to be utmost significant. Flexible manufacturing systems (FMS) have a great potential in manufacturing both cost effective and customer based products. These systems bring us flexibility, but this flexibility accompanies cost and time. Thus, selecting suitable FMS necessitates excessive attention. The problem of FMS selection and evaluation becomes more difficult when facing multi FMSs selection problem. In this paper, we propose an integrated approach to find a suitable combination of FMSs in a multi FMSs decision making problem. Each FMS has several alternatives. Therefore, there are many possible solutions for this problem. We first identify the objective and subjective attributes. Second, Grey system theory is applied to deal with the incomplete and uncertain information of subjective data, and the objective data are extracted from simulation modelling. A goal-programming model is then utilized to formulate the problem and to assign priorities to the objectives. Finally, a genetic algorithm (GA) based model is applied to solve the combination problem, as the formulated problem is difficult to be solved. The model proposed in this paper determines the most appropriate FMSs combination and facilitates decision making of such a hard problem.

Key words: flexible manufacturing systems (FMS), integrated approach, genetic algorithm (GA), grey system theory, goal programming (GP).

1. Introduction

Ever changing customer's needs and rapid market fluctuations lead managers to compete in a fierce global market. In this regard, flexible manufacturing systems (FMS) are used in order to take advantage of their idiosyncratic outcomes. Generally, the concept of flexibility in FMS can be applied to machines, processes, products, routings, volume

* Corresponding author.

or productions. These systems which include interconnected group of processing workstations are called flexible since FMS is capable of processing a variety of different part styles simultaneously at the various workstations (Rao, 2006). A generic FMS can even make a part be processed on a continuous basis without human involvement. This ability enables FMS to be flexible enough to cope with market fluctuations while requiring no new equipment.

In the 21st century, enterprises are approaching to the application of advanced manufacturing technologies. There appears to be a few numbers of factories to be fully automated meaning to manufacture the products without intervening of the human beings. In some of these enterprises, like automobile manufacturers, there are more than one FMS to produce one product since the different modules of the product have various manufacturing technologies. For example, manufacturing the seats of an automobile completely differs from its engine manufacturing process. Thus, they should have separate FMSs to manufacture. These FMSs are interrelated due to their flexibility relationships. Therefore, devising a proper combination of these FMSs necessitates when such decision-making appears. Each FMS has its alternatives. Hence, if we have i.e. four FMSs each of which has five alternatives we have $4 \wedge 5$ possible solutions to find the best or even near optimum FMSs combination for the factory as the four FMSs are in relation with each other with respect to their flexibility. Therefore, finding a suitable alternative for each FMS, considering several objectives; cost, quality, etc., in order to meet both customers and manufacturer requirements is a challenging task. To reach the objective, providing a suitable model is necessary to assure the success of the manufacturing process and to estimate the optimum FMSs combination. Thus, a set of different combinations among the many possible solutions should be generated and the best one selected in the minimum possible time to help decision makers in the decision process. In this paper, an effective mathematical model based goal programming, solving by GA technique, is proposed for the problem of FMS selection in an uncertain environment considering both subjective and objective factors.

2. Literature Review

The FMS received much attention over the last 25 years. In the last decade, they became significant elements in the success of enterprises (Candan and Yazgan, 2015). As a complex dynamic system, FMS is extremely important to optimize the productivity by utilizing the available resources (Jyothi, 2012). Rao (2013) summarizes the benefits of FMS in three basic achievements: increasing in product types, enhancement in quality and reduction in WIP and setup costs. FMS aims to provide greater manufacturing flexibility, less inventory and floor space, lower lead times, and longer useful life of equipment over consecutive generations of different products (Kulak and Kahraman, 2005). That is why FMSs have received great attention for over three decades. Due to increased attention and investment on FMS technologies, the evaluation process for selecting the proper technologies requires a logical systematic mathematical approach to make the best decision to be conjugated with real requirements. Tao *et al.* (2015) provide a tri-view

model established to analyse the evolution and socialization characteristics of advance manufacturing systems. FMS selection, as a complicate multi criteria decision making problem, requires a robust decision support system to consider both monetary and non-monetary criteria. Being multidimensional situations, these problems can be solved by various techniques (Chakraborty *et al.*, 2015). Stam and Kuula (1991) proposed a two-phase decision model using AHP to reduce the number of alternatives and provided a multi-objective mathematical programming model to select the most suitable FMS. Shang and Sueyoshi (1995) proposed an evaluation procedure incorporating the AHP (analytical hierarchy process), simulation, and DEA for the selection of FMS alternatives. Khouja (1995), Karsak (2008), and Liu (2008) applied Data Envelopment Analysis (DEA) to evaluate and to select FMSs. Multi criteria decision making (MCDM) tools are prevalent techniques used to justification of advanced manufacturing technologies (AMTs) (Chuu, 2009; Karsak and Tolga, 2001). Singh *et al.* (2016) developed an analytic hierarchic process to analyse FMS. In the last few decades, a great number of researches have focused on the selection methodologies. We refer the readers to Chatterjee and Chakraborty (2014) providing a review on advance manufacturing technology selection based on MCDM techniques.

An effective justification process requires the consideration of many quantitative attributes and qualitative attributes. There are various attributes for the evaluation of manufacturing technologies: cost, work in process (WIP), flexibility, quality, yield, floor space, down time, number of employees, expandability, ease of use, competitiveness and so on (Rao and Parnichkun, 2009; Sener and Karsak, 2007; Rao, 2006). Based on the literature reviewed the attributes are classified into two categories: qualitative and quantitative (Chuu, 2009; Ragavan and Punniyamoorthy, 2003; Karsak and Tolga, 2001). There some important parameters such as financial, technological, maintenance and governmental policies in passing to FMS are also provided by Erdin and Atmaca (2015). The detailed attributes used in other studies are collected in Table 1. We can observe that most attributes used nearly by all studies are flexibility, quality, cost (purchase & setup), WIP, Yield or throughput and space required. The factors "Ease of use", Reliability, "Labour reduction", capacity and learning are in less attention in the above mentioned studies.

Among these attributes, the qualitative factors (reliability, quality, etc.) obtained by experts, are not crisp values and include vague and incomplete information. Also, collecting exact data is a difficult task and seldom available.

Fuzzy mathematics and Grey systems theory are two most-often applied theories employed in studies of this kind of uncertainties. The main idea of fuzzy mathematics is based on the membership functions established based on experiences. Thus, a number of previous works on advanced manufacturing technologies' (AMT) justification are based on fuzzy data. Rao and Parnichkun (2009) proposed a fuzzy combinatorial mathematics-based decision-making method for evaluation and ranking of FMS alternatives. Chuu (2009) applied fuzzy multiple attributes group decision making with multiple fuzzy information to select the best FMS alternative in Taiwanese bicycle industry. Karsak and Tolga (2001) developed a fuzzy MCDM approach to evaluate advanced manufacturing system investments applying fuzzy ranking method. Karsak and Kuzgunkaya (2002) proposed a

Table 1
Detailed attributes based on the literature review.

Year and Authors	Flexibility	Quality	Cost	WIP	Yield	Space required	Down time	Labour reduction	Capacity	Ease of use	Learning	Lead time	Reliability	Tardy job
Chakraborty <i>et al.</i> (2015)		*	*	*		*								
Chatterjee and Chakraborty (2014)	*	*	*	*		*						*		
Mandal and Sarkar (2012)	*	*	*									*		
Rao and Parnichkun (2009)	*	*	*			*				*				
Chuu (2009)	*	*	*			*			*		*	*		
Anvari <i>et al.</i> (2010)		*	*	*	*	*							*	*
Karsak (2008)	*	*	*	*	*	*						*		
Liu (2008)		*	*	*	*	*								*
Sener and Karsak (2007)	*		*	*	*	*	*							
Rao (2006)	*	*	*		*	*		*						
Karsak and Kuzgunkaya (2002)		*	*	*		*								
Luong (1998)	*	*		*	*							*		
Shang and Sueyoshi (1995)		*	*	*	*	*								*

multiple objective programming approach based on fuzzy data to the selection of a proper FMS. Rao (2007) suggested a fuzzy decision methodology based on digraph and matrix methods to facilitate the selection of a suitable flexible manufacturing system. Liu (2008) presented a fuzzy DEA/assurance region (AR) method capable of measuring the performance of FMS alternatives by crisp and fuzzy data for the representation of inputs and outputs.

The Grey systems theory, proposed by Deng (1985), is developed to study problems of “small samples and poor information” and requires neither frequent distributions nor exact membership functions. Also, grey theory – as the expansion of fuzzy theory (Jun, 1993) – considers the condition of the fuzziness and deal flexibly with fuzzy situation (Tseng, 2008). Applying this theory to the problem of FMSs selection has been seen in a few references. A fuzzy MCDM approach based on the concept grey systems theory has been proposed by Dhal *et al.* (2011) to systematically evaluate FMSs’ alternatives. In another research, Samvedi *et al.* (2011) applied fuzzy AHP, grey relation analysis to rank the FMS’s tools.

To the best of our knowledge, among all these researches, there exists a lack of proper solution when we have multi FMSs combination selection problem. In many manufacturing companies such as automobile manufacturers, there are more than one FMS to be selected when the sequencing is not a matter and when there are flexibility relations between the alternatives of different FMSs items. In this study, we propose a GA based grey system theory decision frame work to select the proper combination of multi FMSs in a factory. GA is applied to select the near optimal solution as a quick response tool in this complicated problem. Both qualitative and quantitative attributes are applied for this selection problem. Each possible solution is assessed through a mathematical model using these attributes. The attributes considered as objectives are: cost (investment and maintenance cost), decrease in WIP (work in process), decrease in the number of tardy jobs, improvement in quality, space required, reliability and Yield (as throughput minus scrape

and rework). Since the qualitative data accompanies incomplete information based on the experts' scores and unavailability of exact and crisp data and cannot be estimated by an exact numerical value, we use the Grey systems theory in this selection problem.

The organization of the paper is as follows: Section 2 describes a complete description on the multi FMS selection problem. In Section 3, the preliminaries of methodologies applied to solve the problem are explained. Section 4 presents the proposed approach. In Section 5 an illustrative example is developed to show the validity of the proposed model. Finally, Section 6 contains a brief conclusion on the discussed issues.

3. Preliminaries

3.1. Genetic Algorithm (GA)

The theory of Genetic Algorithms (GA) is initially proposed by Holland (1975) as a probabilistic search method in an attempt to emulate Darwin theory of natural selection which is the basic manifest of the most fitting survival. GA is operated to optimize a population of candid solutions; each one presented by a string containing random numbers, by modification the characteristics of the set of solutions. It is able to provide the capacity of sectioning the optimum solution according to problem specifications, whether the criteria of concern are nonlinear, constrained, multi-modal, discrete, or NP hard (Man *et al.*, 1999).

The GA as a parallel processing mechanism takes searches simultaneously in multiple starting points and for different areas, and since it is run based on continuous evolution of generations it is able to increase the speed of finding an optimal solution (Lin *et al.*, 1995). In this regard, it is conclusive to apply GA in finding an optimal solution for multi FMS selection in which the alternatives are interrelated enough to render overly difficult problems.

Conventional GA is operated stepwise based on some general rules to produce, stop, and replicate generations. First of all some random numbers are produced and the gene serial values are set to them to create the initial population. Then a fitness function is defined; mainly acting as the performance indicator of GA it orders the fitness as the basic evaluation criterion in GA, to the extent that if a higher solution is fitted to the fitness function, it takes more chance to survive in next generations. Then it is required to set a stop criterion, by using the fixed number of generations the termination criterion is provided. The replication rule is created to continue the iterative process; and finally crossover and mutation rates are provided, one to acquire and one to avoid. Crossover procedure aims to acquire two descendants with probability of crossover (P_C). The algorithm is summarized as follows:

- Step 1.** Select a random initial population;
- Step 2.** Calculate the fitness function for individual strings and generate new population;
- Step 3.** Mate randomly the members of population and apply the crossover operation for each pair of strings;
- Step 4.** Select a string randomly and carry out the mutation to obtain a new string;

Step 5. Set the stopping condition, calculate the fitness function and select the string with the highest fitness as the solution.

3.2. Grey System Theory

Grey systems theory is one of the new mathematical theories effectively used to solve uncertainty problems with discrete data, incomplete samples and imprecise information (Tseng, 2008). The darkness of colours is generally used to display the degree of information clarification. Accordingly, in Grey systems theory all systems are categorized into three: white, grey, and black groups. The white parts show deterministic and clear information in a system, while the black part has completely uncertain characteristics (Deng, 1984). Hence, the grey parts inherently include insufficient information which stays between two sharp boundaries. Therefore, a grey number $\otimes G$ can be specified by a closed interval including upper and lower limits $[\underline{\mu}_G(x), \overline{\mu}_G(x)]$. This method fulfils the expression of uncertain information when it is difficult to identify the probability density and the membership functions (Chang et al., 1996). The definition of Grey number is as follows.

Let X be the universal set. Then a grey set G of X is defined by its two mappings as $\otimes G = [\underline{\mu}_G(x), \overline{\mu}_G(x)]$ in which $\overline{\mu}_G(x) : x \rightarrow [0, 1]$ and $\underline{\mu}_G(x) : x \rightarrow [0, 1]$ and $\underline{\mu}_G(x) \leq \overline{\mu}_G(x)$, $x \in X$. $\overline{\mu}_G(x)$ and $\underline{\mu}_G(x)$ are the upper and lower membership functions in G respectively. When $\overline{\mu}_G(x) = \underline{\mu}_G(x)$, the grey set G becomes a fuzzy set. It shows that Grey systems theory considers the condition of the fuzziness and can deal flexibly with the fuzziness situation.

The operations on Real numbers can be extended to Grey numbers which are defined on sets of Intervals (Moore, 1966). Suppose Grey numbers are $\otimes G_1 = [\underline{G}_1, \overline{G}_1]$ and $\otimes G_2 = [\underline{G}_2, \overline{G}_2]$, then the basic operations on grey numbers are defined as follows (Wu et al., 2005):

$$\otimes G_1 + \otimes G_2 = [\underline{G}_1 + \underline{G}_2, \overline{G}_1 + \overline{G}_2], \quad (1)$$

$$\otimes G_1 - \otimes G_2 = [\underline{G}_1 - \overline{G}_2, \overline{G}_1 - \underline{G}_2], \quad (2)$$

$$\begin{aligned} \otimes G_1 \times \otimes G_2 \\ = [\min(\underline{G}_1 \underline{G}_2, \underline{G}_1 \overline{G}_2, \overline{G}_1 \underline{G}_2, \overline{G}_1 \overline{G}_2), \max(\underline{G}_1 \underline{G}_2, \underline{G}_1 \overline{G}_2, \overline{G}_1 \underline{G}_2, \overline{G}_1 \overline{G}_2)], \end{aligned} \quad (3)$$

$$\otimes G_1 \div \otimes G_2 = [\underline{G}_1, \overline{G}_1] \times \left[\frac{1}{\underline{G}_2}, \frac{1}{\overline{G}_2} \right], \quad (4)$$

$$k \cdot \otimes = [k \underline{G}_1, k \overline{G}_2]. \quad (5)$$

3.2.1. Determining the Weights of Attributes

Grey theory can effectively be utilized in order to calculate the attribute weights of incomplete information gathered from subjective judgements of DMs (decision makers). This procedure that can be employed instead of pair-wise comparisons (commonly used in Analytic Hierarchy Process) decreases the number of questions that must be answered by DMs. Therefore, considering a large number of qualitative attributes the grey based

Table 2
The scale of attribute weights.

Scale	VL (very low)	L (low)	ML (middle low)	M (middle)	MH (middle high)	H (high)	VH (very high)
$\otimes W$	[0.01, 0.1]	[0.1, 0.3]	[0.3, 0.4]	[0.4, 0.6]	[0.6, 0.7]	[0.7, 0.9]	[0.9, 1.0]

techniques are more efficient in comparison with the traditional MADM techniques such as AHP (Dabbaghi *et al.*, 2010).

3.2.2. Definition of Grey Linguistic Variables

The linguistic variables are used to represent imprecision of data and DMs’ preferences over the attributes in the evaluation process. In this research, the attribute weights are considered as linguistic variables. These linguistic variables can be expressed in grey numbers by the 1–7 scales, concerning Dabbaghi *et al.* (2010), as shown in Table 2.

3.2.3. General Procedure of Calculating Weights

Assume that $Q = \{Q_1, Q_2, \dots, Q_r\}$ is a set of n attributes of FMS evaluation and the attributes are additively independent. $\otimes w_1, \otimes w_2, \dots, \otimes w_n$ is the vector of attribute weights. Suppose that the decision group consists of k persons. According to Geometrical Mean for Grey numbers, the weight of the j -th attribute can be calculated as:

$$\otimes w_j = \sqrt[k]{\otimes w_j^1 \times \otimes w_j^2 \times \dots \times \otimes w_j^k} \tag{6}$$

where $\otimes w_j^k$ ($j = 1, 2, \dots, n$) is the subjective judgement of the k -th DM over the j -th attribute described by grey numbers $w_j^k = [\underline{w}_j^k, \overline{w}_j^k]$; where $\underline{w}_j^k \neq 0$.

Focusing on the most important attributes can facilitate the evaluation process. In order to remove the attributes which are not essentially important we suggest and employ the following definition.

3.3. Goal Programming (GP)

Goal Programming (Lee, 1972) has been widely applied to solve different real-world problems which involve multiple objectives. Goal programming (GP) is designed to deal with problems involving multiple conflicting objectives. However, to overcome the drawback of GP, decision-makers must specify their goals and priorities beforehand. A systematic procedure is needed to determine the following factors in constructing the GP model through group discussion: (1) objectives, (2) desired level of attainment for each objective, (3) degree of interdependent relationships, and (4) penalty weights for overachievement or underachievement of each goal (Chang *et al.*, 2009). The optimal configuration of decision variables (parameters) minimizes the sum of weighted penalties subject to a series of technological and managerial constraints (Azadeh *et al.*, 2010).

4. Proposed Approach

In order to find a solution for the FMSs combination problem, we used genetic algorithm in combination with Grey systems theory approach to solve this multi objective selection problem. Usually we might only face the FMS selection problems for a factory, which is previously solved by many researchers, but also it is possible to face multi FMSs combination selection problem. In a multi FMS combination problem, each FMS consists of several alternatives. In order to find the optimum FMS combination, we have to consider many solutions and in some cases the problem becomes NP-hard. How much more the size of the problem increases, the problem becomes more difficult. In this case, using a well-known Meta heuristic algorithm, i.e. genetic algorithm (GA), is applicable. GA is utterly successful in solving such problems. Also, the formulated problem would be very difficult to be solved if the factory has a structure with a large number of FMSs, and thus it would be troublesome to be solved by linear programming software, such as Lingo, as the selection problem includes binary flexibility relations. Since the problem is based on multi objectives (cost, yield, WIP, tardy jobs, etc.) and their priorities are also important to be considered, goal programming is applied to minimize the total deviation of each objective from its threshold value and to consider the objectives' priorities. In addition, number of calculations would be reduced since they do not need to be converted to the same scale anymore. Because preference information on attributes of flexible manufacturing systems and on criteria belongs to the DMs' subjective judgements, they cannot be estimated by an exact numerical value, so the Grey systems theory is employed to effectively deal with the recognitive uncertainty environment in the FMSs combination selection problem. Utilizing Grey systems theory does not require assuming any membership function or distribution. In addition, the priorities on both qualitative and quantitative objectives are considered by employing grey numbers. Moreover, the presented approach, which introduces integration of the Grey systems theory to the goal programming and genetic algorithm, effectively works with the grey numbers in the entire evaluation and optimization process and does not require any kind of transformation from grey numbers to crisp values. The steps of the proposed approach are defined as follows:

- Step 1:** Identify the J objective and subjective attributes (indicators) to be considered (economic, strategic, and operational);
- Step 2:** Constitute a group of I decision makers (DM_1, DM_2, \dots, DM_I) to assess the subjective attributes of m FMSs each of which has n alternatives utilizing grey numbers and the geometrical mean as explained in Section 3.2;
- Step 3:** Simulate the current shop(s') situation to obtain the values of non-measurable operational (quantitative) indicators when substituting the new FMSs' alternatives in the shop. Turn the obtained valued into a grey number by adding and subtracting the standard deviation (σ) from the arithmetic mean (μ) to construct an interval for each value $[\mu - \sigma, \mu + \sigma]$;
- Step 4:** Find the J attributes' preference weights using Grey systems theory;
- Step 5:** Minimize the total deviation of attributes from their threshold values using goal programming with the application of grey numbers. This step is the mathematical formulation of the attributes;

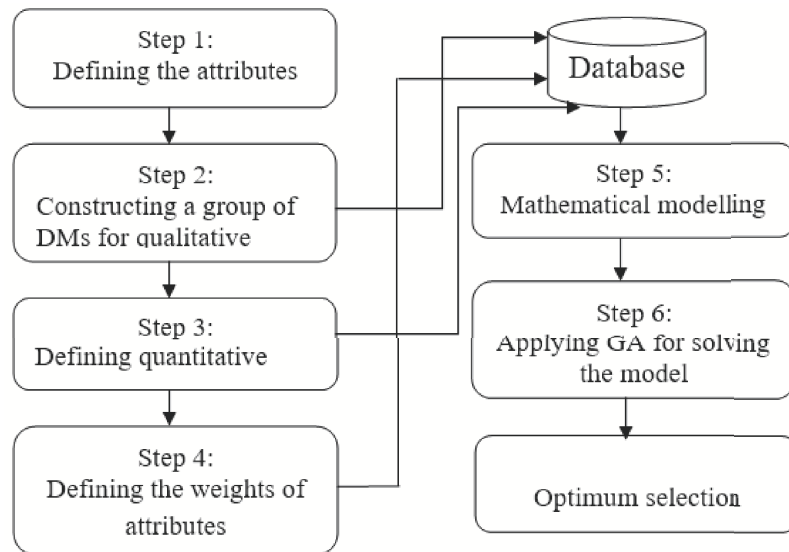


Fig. 1. The schematic diagram of the proposed approach.

Step 6: Apply the genetic algorithm (GA) to solve the multi FMSs combination problem using the mathematical formulation in step 4 as the fitness function to find the proper combination of FMSs.

In all steps, the incomplete information of attributes is expressed using grey numbers as described in Section 3.2.

5. An Illustrative Example

In this section, the proposed approach is applied to a practical case using the described steps in order to find a proper FMS combination. Figure 1 shows the steps schematically in brief.

Step 1. In this example, we first identified and then applied the following indicators for the evaluation under study:

- Operational indicators: yield which is the throughput minus scrap and rework (Shang and Sueyoshi, 1995), work in process (WIP), the number of tardy jobs.
- Strategic indicators include space required for each FMS, reliability of the selected FMSs combination, percent of improvement in quality and flexibility.
- Flexibility is assumed as a significant factor to make the relation of the FMSs in each combination. Flexibility includes system flexibility, volume flexibility, expansion flexibility, routing flexibility, process flexibility and product flexibility.
- Economic indicators: we applied cost including both initial investment and average maintenance costs.

Table 3
An illustrative example of expert linguistic judgements for quality index values of FMS₁ alternatives.

Experts	FMS11		FMS12		FMS13		FMS14		FMS15	
DM1	F		MG		P		F		VG	
DM2	MP		F		MP		G		G	
DM3	MG		G		MP		G		VG	
DM4	G		G		P		MG		G	
DM1	4	6	6	7	1	3	4	6	9	10
DM2	3	4	4	6	3	4	7	9	7	9
DM3	6	7	7	9	3	4	7	9	9	10
DM4	7	9	7	9	1	3	6	7	7	9
Average	4.74	6.24	5.86	7.64	1.73	3.46	5.86	7.64	7.94	9.49

Table 4
Flexibility relation matrix.

	FMS1	FMS2	FMS3	FMS4
FMS1	0	1	0	1
FMS2	1	0	1	0
FMS3	0	1	0	1
FMS4	1	0	1	0

Step 2. A group of four decision makers (DM) from the top managers are constructed to evaluate the 4 FMSs that each of them is assumed to have 5 alternatives. Totally, 20 FMSs' alternatives are assessed by the selected experts to make the best decision for replacing the current job shop with new FMSs. Each DM should estimate the linguistic judgement (VL, L, M, etc.) of qualitative attributes utilizing Grey systems theory. Each linguistic expression assigned by a DM is turned into an interval base on Table 2. Then, the interval based geometrical mean of the 4 DMs' decisions on one index is assumed as its value for entering into evaluation. Table 3 shows a typical example of such judgement for FMS1's alternatives. For instance, the first decision maker's (DM1) opinion about the quality index of FMS11 (the 1st alternative of FMS1) is a fair quality for that in the grey systems based on Table 2, it is a number between 4 and 6. Other decisions also follow the same approach. Another subjective attribute pertains to flexibility. We consider flexibility as the relation of the FMSs two by two in a selected combination with regard to their volume flexibilities assessing the related value that how much flexibility relation do they have when, for instance, one of them increases in volume or changes the product. Before applying judgements, we have to demonstrate the relation matrix between the four FMSs. Table 4 indicates the flexibility relation matrix of the four FMSs using 0–1 matrix. 0 depicts no relation and 1 shows that there is a flexibility relation. The same evaluation process occurs for flexibility as well as quality index. Having the flexibility relation with respect to Table 4, the FMSs' alternatives are compared to obtain their subjective flexibility relation values. Table 5 illustrates an example of the calculation of flexibility relation values between FMS1 alternatives and FMS2 alternatives. All the relation values are expressed in grey numbers and collected in Table 6. The calculated values of all judgements for both the qualitative and quantitative factors, are collected in Table 7.

Table 5
An illustrative example of expert’s linguistic judgements of DMs for flexibility relation values between FMS₁ and FMS₂ alternative.

Experts	FMS ₁₁	FMS ₂₁	FMS ₁₁	FMS ₂₂	FMS ₁₁	FMS ₂₃	FMS ₁₁	FMS ₂₄	FMS ₁₁	FMS ₂₅
DM1	VG		MG		G		VG		G	
DM2	F		F		F		G		F	
DM3	G		G		MG		F		G	
DM4	VG		G		VG		G		F	
DM1	9	10	6	7	7	9	9	10	7	9
DM2	4	6	4	6	4	6	7	9	4	6
DM3	7	9	7	9	6	7	4	6	7	9
DM4	9	10	7	9	9	10	7	9	4	6
Average	6.90	8.57	5.86	7.64	6.24	7.84	6.48	8.35	5.29	7.35

Step 3. After calculation of subjective attributes, it is time to find the values of quantitative factors. It is simple to find some of these attributes such as space required and reliability, which are defined through the information obtained from the FMSs suppliers. We also consider the cost factor, the initial investment and the average maintenance cost for the period of 10 years as calculated in Saidi Mehrabad and Anvari (2009). The cost values are turned into grey numbers as the cost estimation is not crisp. Since finding the real changes in the number of tardy jobs, WIP and yield are difficult after replacing the new FMSs combination with the existing equipments, these values should be extracted by simulation. Thus, percent decrease in the number of tardy jobs, percent decrease in WIP, and Yield are assumed to be obtained from simulation study presented by Saidi Mehrabad and Anvari (2009) and Shang and Sueyoshi (1995). The attained values are turned into grey numbers to deal with their uncertainty as illustrated in Table 7. Each FMS is assumed to have five alternatives to be selected by DMs.

Step 4. In order to find the weights of indicators, we utilize the Grey systems theory along with the expert judgements based on the explanation presented in Section 3.2. Each expert indicates his judgement for each alternative’s importance using the subjective statements (VL, L, etc.) in Table 2. The obtained weights indicate the priorities of the objectives and will be used in the next steps as w_i in the minimization function of the goal programming model. Table 8 represents the weights all in grey numbers.

Step 5. We constructed a mathematical model for FMSs combination selection problem in which cost, Yield, WIP, number of tardy jobs, required space, quality, reliability and flexibility are taken into consideration. The notations used to develop the mathematical model for this selection problem are as follows.

Parameters of the model and notation

Since GA will be applied for solving the selection problem, the indicators for each FMS, alternatives of the FMSs should be identified. Additionally, some of the other notations for the specified attributes should also be defined as grey variables:

- i, ℓ : FMS indicators, $i = 1, 2, 3, \dots, I, \ell = 1, 2, 3, \dots, L$;
- j, k : FMS’s alternative index, $j = 1, 2, 3, \dots, J, k = 1, 2, 3, \dots, K$;
- I, L : total number of FMSs;

Table 6
Values of flexibility relation matrix between FMSs' alternatives.

	FMS21	FMS22	FMS23	FMS24	FMS25	FMS31	FMS32	FMS33	FMS34	FMS35	FMS41	FMS42	FMS43	FMS44	FMS45
FMS11	[6.9, 8.57]	[5.85, 7.63]	[6.23, 7.48]	[6.48, 8.34]	[5.29, 7.34]						[7.17, 8.67]	[0.14, 2.05]	[6.9, 8.14]	[7.63, 8.9]	[5.63, 7.54]
FMS12	[1.32, 3.22]	[3.83, 5.09]	[5.63, 7.17]	[0.13, 1.86]	[7.17, 8.68]						[5.86, 7.64]	[7.17, 8.68]	[5.86, 7.64]	[2.45, 4.12]	[0.03, 1.32]
FMS13	[1.73, 3.46]	[5.86, 7.64]	[1.86, 3.83]	[2.63, 4.56]	[7.45, 9.24]						[5.85, 7.63]	[6.73, 8.45]	[7.94, 9.48]	[2.45, 4.12]	[1.86, 3.83]
FMS14	[0.59, 2.91]	[6.24, 7.84]	[3.72, 5.42]	[5.09, 6.9]	[8.13, 9.15]						[4.9, 6.48]	[6.09, 8.13]	[0.42, 2.45]	[2.45, 4.12]	[5.63, 7.17]
FMS15	[6.42, 7.75]	[6.48, 8.35]	[2.21, 4.41]	[4.28, 6]	[1.86, 3.83]						[0.32, 2.28]	[4.9, 6.48]	[7.94, 9.49]	[4, 6]	[1.32, 3.22]
FMS21						[4.92, 6.64]	[7.63, 8.9]	[0.54, 2.63]	[3.02, 5.04]	[0.31, 2.27]					
FMS22						[6.64, 8.05]	[5.45, 6.9]	[0.42, 2.45]	[4.28, 6]	[0.17, 2]					
FMS23						[2, 4.24]	[8.45, 9.74]	[2.45, 4.12]	[6.24, 7.45]	[1.73, 3.46]					
FMS24						[6.24, 7.45]	[1.86, 3.83]	[0.17, 2]	[1.32, 3.22]	[4, 6]					
FMS25						[0.13, 1.86]	[5.63, 7.17]	[7.17, 8.68]	[6.64, 7.65]	[2.28, 3.72]					
FMS31											[2.45, 4.12]	[0.42, 2.45]	[6.48, 7.94]	[4.43, 6.24]	[6.24, 7.84]
FMS32											[2.45, 4.12]	[0.55, 2.63]	[6.48, 7.94]	[4.43, 6.24]	[5.09, 6.9]
FMS33											[2.45, 4.12]	[0.59, 2.91]	[6.48, 7.94]	[4.43, 6.24]	[4.9, 6.48]
FMS34											[2.45, 4.12]	[0.42, 2.45]	[6.48, 7.94]	[4.43, 6.24]	[5.86, 7.64]
FMS35											[2.45, 4.12]	[0.42, 2.45]	[6.48, 7.94]	[5.09, 6.9]	[4.43, 6.24]

Table 7
The qualitative and quantitative values of FMSs' alternatives.

FMSs	Alternatives	Cost (\$0000)	Yield (00)	WIP (%)	Tardy jobs (%)	Quality	Space required (ft2)	Reliability
FMS1	FMS11	[115.3, 118.63]	[19.6, 21.4]	[10.1, 12.4]	[4.8, 5.5]	[4.73, 6.24]	4500	0.94
	FMS12	[125.54, 128.2]	[18.5, 20]	[4.2, 5.8]	[8.5, 9.8]	[5.85, 7.64]	5100	0.95
	FMS13	[110.72, 112.47]	[23.5, 25.3]	[7.8, 9.1]	[13, 14.5]	[1.73, 3.46]	5000	0.98
	FMS14	[140.36, 142.75]	[15.4, 16.9]	[8.4, 10]	[15, 16.30]	[5.85, 7.64]	3800	0.9
	FMS15	[111.9, 113.68]	[10, 12.4]	[6.4, 9.3]	[6.8, 7.4]	[7.93, 9.49]	7100	0.98
FMS2	FMS21	[90.82, 93.25]	[29.5, 32.4]	[18.1, 20.6]	[8.89, 20]	[3.03, 5.05]	3400	0.93
	FMS22	[88.34, 90]	[24.5, 26.7]	[10.3, 12.4]	[13.8, 14.20]	[4.74, 6.24]	2700	0.9
	FMS23	[95, 110.42]	[28.6, 31.2]	[9.7, 11.2]	[0, 1.10]	[0.41, 2.45]	4600	0.98
	FMS24	[105.3, 107.4]	[18.3, 21.1]	[19.4, 20.2]	[9.4, 10.30]	[3.72, 5.42]	3000	0.99
	FMS25	[95.476, 98]	[23.5, 25.9]	[7.8, 8.5]	[6.4, 6.80]	[7.63, 8.91]	6500	0.94
FMS3	FMS31	[270, 272]	[15.4, 17.7]	[5.3, 7.8]	[5.3, 6.70]	[7.17, 8.68]	2000	0.99
	FMS32	[293.35, 296]	[13.1, 14.9]	[7.1, 9.5]	[13.1, 14.5]	[5.09, 6.90]	4500	0.98
	FMS33	[261.36, 262.7]	[18.1, 20.3]	[10.1, 11.3]	[2.6, 3.80]	[0.42, 2.45]	3200	0.94
	FMS34	[275.45, 277.68]	[14.5, 16.2]	[8.3, 9.8]	[8.4, 9.70]	[3.72, 5.42]	6000	0.96
	FMS35	[298.47, 300.9]	[10, 13.4]	[4.8, 6.9]	[4.9, 10.50]	[7.637, 8.91]	5000	0.95
FMS4	FMS41	[62.36, 64.8]	[11, 12.3]	[12.6, 13.8]	[16.2, 17.60]	[3.56, 5.38]	7000	0.93
	FMS42	[65.34, 67.45]	[15, 17]	[9.5, 10.9]	[14.6, 15.80]	[5.09, 6.90]	5900	0.9
	FMS43	[51.9, 53]	[20.1, 22]	[11.4, 13.1]	[19, 20.10]	[0.54, 2.63]	6100	0.98
	FMS44	[50.67, 52.19]	[13.3, 15.1]	[8.9, 10.1]	[9.8, 10.70]	[3.72, 5.42]	3800	0.99
	FMS45	[70.872, 56]	[16.7, 19.1]	[7.8, 9.8]	[10.8, 11.90]	[7.63, 8.91]	3200	0.99

Table 8
Priority weights of the attributes or objectives.

Weights of goals	Cost (\$0000)	Yield (00)	WIP (%)	Tardy jobs (%)	Space required (ft2)	Reliability	Quality	Flexibility
	[0.845, 0.97]	[0.90, 1]	[0.49, 0.66]	[0.53, 0.73]	[0.76, 0.89]	[0.65, 0.83]	[0.59, 0.76]	[0.845, 0.97]

- J_i, K_ℓ : total number of FMSs alternatives available for FMS i, ℓ ;
- $\otimes C_{ij} = [\underline{C}_{ij}, \overline{C}_{ij}]$: initial investment together with maintenance cost for alternative j of FMS $_i$;
- $\otimes Q_{ij} = [\underline{Q}_{ij}, \overline{Q}_{ij}]$: percent improvement in quality by alternative j of FMS $_i$;
- $\otimes WIP_{ij} = [\underline{WIP}_{ij}, \overline{WIP}_{ij}]$: percent improvement in alternative j of FMS $_i$;
- $\otimes YD_{ij} = [\underline{YD}_{ij}, \overline{YD}_{ij}]$: yield of alternative j of FMS $_i$ when replacing with old equipments;
- $\otimes TJ_{ij} = [\underline{TJ}_{ij}, \overline{TJ}_{ij}]$: percent decrease in number of tardy jobs of alternative j of FMS $_i$;
- $\otimes FLEX_{il}^{jk} = [\underline{FLEX}_{il}^{jk}, \overline{FLEX}_{il}^{jk}]$: flexibility relation value for alternatives j, k of FMSs i, ℓ ;
- REL_{ij} : reliability for alternative j of FMS $_i$;
- SR_{ij} : space required for alternative j of FMS $_i$;
- $\otimes TC$: total costs of an FMSs combination provided by the selected alternatives;
- $\otimes TQ = [\underline{TQ}, \overline{TQ}]$: total quality improvement of an FMSs combination provided by the

- selected alternatives;
 $\otimes TYD = [\underline{TYD}, \overline{TYD}]$: total yield of an FMSs combination provided by the selected alternatives;
 $\otimes TTJ = [\underline{TTJ}, \overline{TTJ}]$: total decrease in number of tardy jobs of an FMSs combination provided by the selected alternatives;
 $\otimes TFLEX = [\underline{TFLEX}, \overline{TFLEX}]$: total flexibility of the selected FMSs;
 $\otimes TWIP = [\underline{TWIP}, \overline{TWIP}]$: total decrease in WIP of the selected FMSs;
 $\otimes TTTJ = [\underline{TTTJ}, \overline{TTTJ}]$: total decrease in number of tardy jobs of the selected FMSs;
 $TREL$: total reliability of an FMSs combination provided by the selected alternatives;

Objective function

Equation (7) shows the objective function minimizing the total deviation of the objectives (Cost, Yield, WIP, etc.) as the objectives pertain to the FMSs' alternatives from their acceptable thresholds (d_i is deviation from desired level of the objectives and i is the number of objectives, w_i are the weights obtained in Step 4):

$$\begin{aligned} & \text{Minimize } \otimes Z, \\ \otimes Z &= \sum_{i=1}^8 \otimes w_i \times \otimes d_i. \end{aligned} \quad (7)$$

Constraints

Equation (8) shows the total cost as a grey number. The total cost is the sum of initial investment and average maintenance of all FMS's alternative in a selected combination:

$$\otimes TC = \sum_{i=1}^I \sum_{j=1}^{J_i} (\otimes C_{ij} \times Y_{ij}), \quad i \neq l. \quad (8)$$

Equation (9): total flexibility relation value as a grey number. Displays the total flexibility relationships between the FMSs' alternatives for a selected FMS combination:

$$\otimes TFLEX = \sum_{i=1}^I \sum_{j=1}^{J_i} \sum_{l=1}^I \sum_{k=1}^{k_l} (\otimes FLEX_{il}^{jk} \times X_{il}^{jk} \times Y_{ij} \times Y_{ilk}), \quad i \neq l. \quad (9)$$

Equation (10) shows the total decrease in WIP as a grey number. The total decrease in WIP is the sum of this value of FMSs from all selected alternatives:

$$\otimes TWIP = \sum_{i=1}^I \sum_{j=1}^{J_i} (\otimes WIP_{ij} \times Y_{ij}). \quad (10)$$

Equation (11). Total tardy job is the total percent decrease in the number of tardy jobs in the existing job shop's products when replacing with new FMSs combination:

$$\otimes TTJ = \sum_{i=1}^I \sum_{j=1}^{J_i} (\otimes T J_{ij} \times Y_{ij}), \quad i \neq l. \tag{11}$$

Equation (12). Total yield is the sum of yield for a selected FMSs combination:

$$\otimes TYD = \sum_{i=1}^I \sum_{j=1}^{J_i} (\otimes Y D_{ij} \times Y_{ij}). \tag{12}$$

Equation (13). Total quality is the sum of improvement in the quality level of the existing job shop's products when replacing with new FMSs combination. This qualitative factor is considered as a grey number to deal with its uncertain information:

$$\otimes TQ = \sum_{i=1}^I \sum_{j=1}^{J_i} (\otimes Q_{ij} \times Y_{ij}), \quad i \neq l. \tag{13}$$

Equation (14). Total reliability is the multiple of the reliability (REL) of FMSs from all alternatives in a selected combination as they assumed to be a series system:

$$TREL = \prod_{i=1}^I (REL_{ij} \times Y_{ij}). \tag{14}$$

Equation (15). Total space required is the sum of the space each FMS required in a combination:

$$TSR = \sum_{i=1}^I \sum_{j=1}^{J_i} (SR_{ij} \times Y_{ij}). \tag{15}$$

Constraints (16)–(23) indicate the deviation of the goals from the threshold values which is minimized through the objective function (1). The right hand side values are obtained by experts' judgement:

$$\otimes TC - \otimes d_1 = [500-530], \tag{16}$$

$$\otimes TFLEX - \otimes d_2 = [90-100], \tag{17}$$

$$\otimes TWIP - \otimes d_3 = [60-80], \tag{18}$$

$$\otimes TTJ - \otimes d_4 = [60-80], \tag{19}$$

$$\otimes TYD - \otimes d_5 = [95-100], \tag{20}$$

$$\otimes TQ - \otimes d_6 = [50-60], \tag{21}$$

$$TREL - d_7 = 1, \quad (22)$$

$$TSR - d_8 = 11000, \quad (23)$$

$$X_{il}^{jk} = \begin{cases} 1, & \text{alternative } j \text{ of FMS}_i \text{ has flexibility relation with FMS}_l \text{ of alternative } k \\ 0, & \text{otherwise,} \end{cases}$$

$$Y_{ij} = \begin{cases} 1, & \text{alternative } j \text{ of FMS}_i \text{ is selected,} \\ 0, & \text{otherwise,} \end{cases} \quad \text{for all } i, j, \quad (24)$$

$$Y_{lk} = \begin{cases} 1, & \text{alternative } j \text{ of FMS}_i \text{ is selected,} \\ 0, & \text{otherwise,} \end{cases} \quad \text{for all } l, k. \quad (25)$$

Constraints (26), (27) show that only one alternative can be selected for each FMS:

$$\sum_{j=1}^{J_i} Y_{ij} = 1, \quad \text{for all } i, j, \quad (26)$$

$$\sum_{k=1}^{K_\ell} Y_{\ell k} = 1, \quad \text{for all } \ell, k. \quad (27)$$

The above assessment formulated model is very difficult to solve if the FMSs has a structure with a large number of alternatives. For this reason, a genetic algorithm based approach is developed to process this assessment model through the illustrated evaluation tables.

Step 6. After collecting data for multi FMSs selection, the genetic algorithm is applied to solve the proposed mathematical model. The collected data are inserted into the mathematical model and the model works as an evaluation function in the GA. We used MATLAB R2014 software to apply the real coding to find the proper solution for FMSs combination selection problem. The general steps of GA we followed in this study are stated below:

(1) Generate initial population.

Each chromosome in the initial population represents a possible FMSs combination in the factory. Each gene indicates a possible alternative for an FMS. We assume to have 4 FMSs and each FMS has 5 alternatives. Thus, there should be 4 genes accordingly in each chromosome and its value can change in the range of 1–5. The following chromosome is an example of a possible solution for multi FMS selection. The chromosome shows that alternatives 3, 1, 5 and 3 are selected for each FMSs of 1–4, respectively. In this study, we tested various numbers of initial populations.

FMS items	FMS1	FMS2	FMS3	FMS4
Alternatives	FMS13	FMS21	FMS35	FMS43

(2) Evaluate fitness function of each chromosome.

For each chromosome, a grey number ($\otimes Z$), representing the total deviation of each FMSs combination from the ideal values based on the mathematical model, is calculated

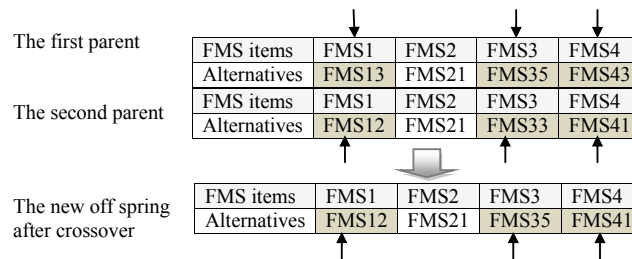


Fig. 2. Uniform crossover.

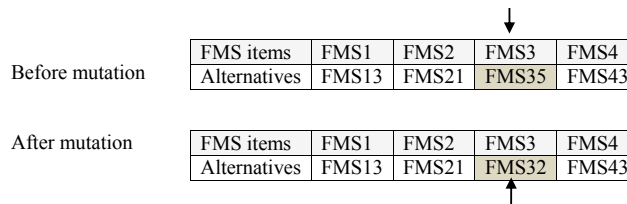


Fig. 3. Single point mutation.

as the fitness function. All the equations (3)–(24) are applied in the computation. Each chromosome that does not meet all the constraints will not be allowed to enter into the population. Hence, the pop will remain feasible.

(3) Select 4 random chromosomes from population for tournament selection.

In order to select a parent for crossover and mutation, we need to select them from the population pool. We applied the tournament selection. 4 chromosomes are selected and they should be compared with each other two by two. The two chromosomes with minimum deviations (Z) will be selected as the parents that crossover should be applied on.

(4) Apply crossover to the selected parents to produce new offspring.

Uniform crossover is adopted for crossing the selected parents (two chromosomes in each generation) in order to generate a new offspring. The procedure is that each gene of the two selected parents is compared one by one. If they are identical, the same alternative will be settled in that gene. If they differ, one of the FMSs' alternatives will be chosen by the probability of 0.5. The process goes on until reaching the end of the chromosomes. Figure 2 illustrates the crossover procedure.

(5) Apply mutation to the new offspring.

The new offspring is then ready for mutation. Single point mutation is adopted. First, a number between 1 and 4 is randomly selected. Then, the randomly selected gene is mutated based on the FMSs' number of alternatives range of the selected gene (1–5). A random number in that range is generated to be replaced by the original number. Figure 3 shows the mutation procedure. Assume that 3 is the selected random number shown by an arrow. This FMS has 5 alternatives. Thus, a random number between 1 and 5 is then selected to replace this alternative. If 2 is selected 5 will be replaced by 2. It is notable that mutation is applied on the chromosome selected from tournament selection.

(6) Enter the new offspring to the population utilizing replacement strategy.

The new offspring is replaced with the worst chromosome (the maximum fitness, Z) in the population that is sorted based on their Z values.

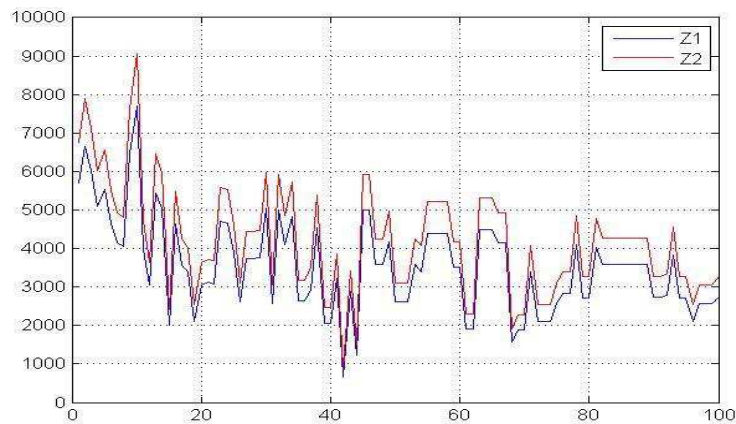


Fig. 4. GA convergence to the interval of $[z1, z2]$ – generation 100-popsize 50.

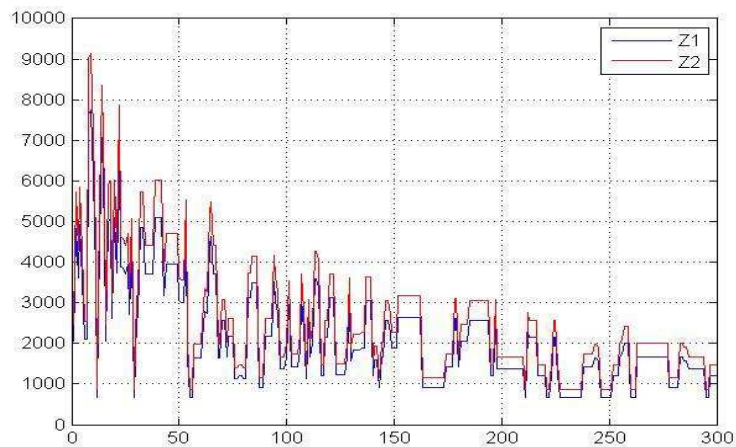


Fig. 5. GA convergence to the interval of $[z1, z2]$ – generation 300-popsize 50.

(7) Stopping condition.

Stopping condition used in this study is based on the number of generations which can be randomly generated from the system interface. Thus, the initial setting and the number of generations must be entered before running the genetic algorithm. Termination occurs when the number of iterations reaches the set number of generations.

We set 100, 200, 300 and 400 as the number of generation in the program together with the different initial populations; 20, 50. Satisfying the stopping condition, the GA procedure will be continually repeated. Figures 4–7 illustrate the comparable results of separate GA implementation based on the generations of 100, 200, 300, 400 and the pop size of 50. GA converges to the interval of $\otimes Z = [680.8, 862.89]$ as a grey number for the generations of 200 and above it. For generation 100 the obtained intervals of the objective function values were in a higher range of total deviation. Thus, for this case we found the 4 2 1 5 as a suitable combination for FMSs. Which means alternative 4 is selected for FMS1, alternative 2 for FMS2, alternative 1 for FMS3 and alternative 5 is selected for

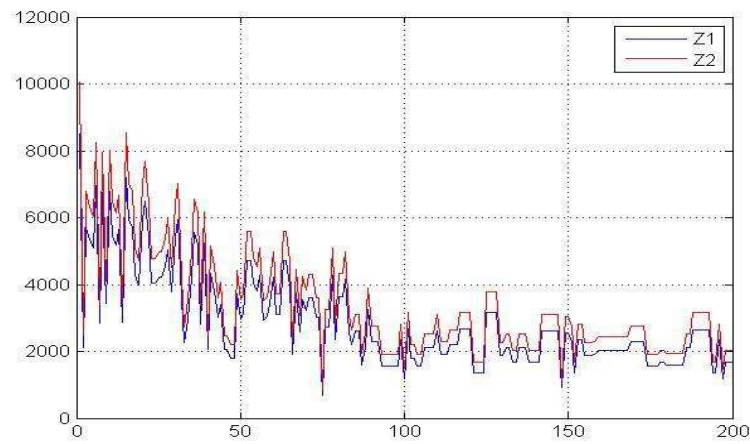


Fig. 6. GA convergence to the interval of $[z_1, z_2]$ – generation 300–popsize 50.

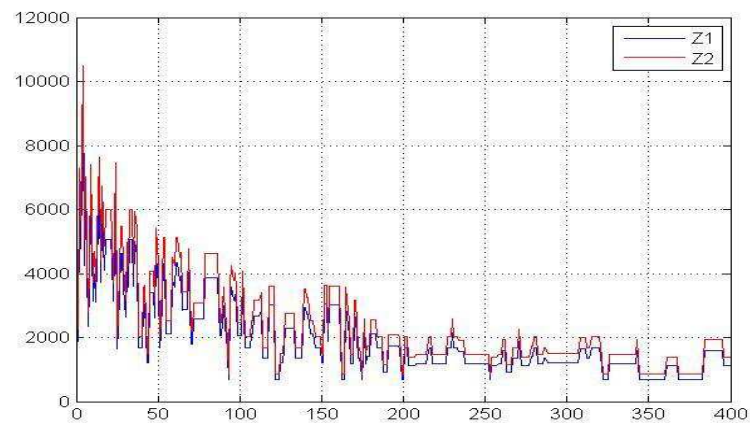


Fig. 7. GA convergence to the interval of $[z_1, z_2]$ – generation 400–popsize 50.

FMS4. The achieved interval for Z , as a grey number, facilitates decision making for the managers as they can find other combinations for this selection problem provided that the results lie within this interval.

6. Conclusions and Further Work

This paper considers a new problem for sustainable flexible manufacturing systems selection and evaluation. All previous works provided numerous solutions to the problem of FMS selection when having one FMS with different alternatives. But we raised a new problem of FMS decision making when there are more than one FMS to be selected in a manufacturing enterprise. Thus, a proper combination of FMSs should be selected. Each of these FMSs has several alternatives with the flexibility relations with other FMSs' alternatives. Therefore, we have developed a goal programming to formulate this problem. The subjective data were obtained by the experts' judgements based Grey systems theory to

deal with the incomplete information of the qualitative attributes. Then a GA based model is adopted to solve this difficult decision making problem. An illustrative example adopted from a real automobile manufacturing (with some changes in data) is developed to test the validity of the proposed model. A group of four decision makers (DM) were constructed to evaluate the 4 FMSs, that each one is assumed to have 5 alternatives. The problem can be solved easily for each alternative separately if the relation between the alternatives is not considered. But there is flexibility relation between alternatives that makes the problem solving more difficult than usual. Consequently, GA was used to solve the problem easily. The outputs of the proposed approach have presented the nearly best alternative for each of the FMSs evaluated based on both objective and subjective attributes simultaneously.

The results show that by means of this approach, we can effectively offer a faster overall evaluation speed, moreover, the utilization of the Grey systems theory can put the results in intervals facilitating decision making as the manager can change the adopted result to other possible combinations, based on their experience, provided that the solution lie within the achieved optimal interval. Additionally, from the sustainability point of view, the proposed approach helps manufacturers to purchase flexible systems considering the systems relations with each other and to manufacture the products in a flexible way with a better quality, less costs and less reworks than before. Future research can include an extension of the developed approach to more complex problems such as combination problems involving FMSs sequence consideration.

References

- Anvari, M., Mehrabad, M.S., Barzinpour, F. (2010). Machine-part cell formation using a hybrid particle swarm optimization. *The International Journal of Advanced Manufacturing Technology*, 47(5–8), 745–754.
- Azadeh, A., Ghaderi, S.F., Dehghanbaghi, M., Dabbaghi, A. (2010). Integration of simulation, design of experiment and goal programming for minimization of make span and tardiness. *International Journal of Advanced Manufacturing Technology*, 46, 431–444.
- Candan, G., Yazgan, H.R. (2015). Genetic algorithm parameter optimisation using Taguchi method for a flexible manufacturing system scheduling problem. *International Journal of Production Research*, 53(3), 897–915.
- Chakraborty, S., Zavadskas, E.K., Antucheviciene, J. (2015). Applications of WASPAS method as a multi-criteria decision-making tool. *Economic Computation and Economic Cybernetics Studies and Research*, 49(1), 5–22.
- Chang, N.B., Wen, C.G., Chen, Y.L., Yong, Y.C. (1996). A grey fuzzy multi objective programming approach for the optimal planning of a reservoir watershed. Part A: Theoretical development, *Water Research*, 10, 2329–2334.
- Chang, Y.H., Wey, W.M., Tseng, H.Y. (2009). Using ANP priorities with goal programming for revitalization strategies in historic transport: a case study of the Alishan Forest Railway. *Expert Systems with Applications*, 36, 8682–8690.
- Chatterjee, P., Chakraborty, S. (2014). Flexible manufacturing system selection using preference ranking methods: a comparative study. *International Journal of Industrial Engineering Computations*, 5, 315–338.
- Chuu, S. J. (2009). Selecting the advanced manufacturing technology using fuzzy multiple attributes group decision making with multiple fuzzy information. *Computers & Industrial Engineering*, 57, 1033–1042.
- Dabbaghi, A., Malek, A. M., Aulizadeh, A. R. (2010). Evaluating the quality of corporate mission statements. In: *Proceedings of the 6th International Strategic Management Conference*, Russia.
- Deng, J. (1984). *The Theory and Methods of Socio-Economic Grey Systems*. Science Press, Beijing (in Chinese).
- Deng, J.L. (1985). Special issue of grey system approach. *Fuzzy Mathematics*, 5, 43–50.
- Dhal, P.R., Datta, S., Mahapatra, S.S. (2011). Flexible manufacturing system selection based on grey relation under uncertainty. *International Journal of Services and Operations Management*, 8, 516–534.

- Erdin, M.E., Atmaca, A. (2015). Implementation of an overall design of a flexible manufacturing system. *Procedia Technology*, 19, 185–192.
- Holland, J.H. (1975). *Adaptation in Natural and Artificial Systems*. The University of Michigan Press, Ann Arbor.
- Jun, X. (1993). A grey system approach applied to prediction of extreme hydrological events: floods and droughts. In: *Extreme Hydrological Events: Precipitation, Floods and Droughts. Proceedings of the Yokohama Symposium*, Vol. 13. IAHS Publ., pp. 447–454.
- Jyothi, S.D. (2012). *Scheduling Flexible Manufacturing System using Petri-nets and Genetic Algorithm*. Project report. Indian Institute of Space Science and Technology, Thiruvananthapuram.
- Karsak, E.E. (2008). Using data envelopment analysis for evaluating flexible manufacturing systems in the presence of imprecise data. *International Journal of Advanced Manufacturing Technology*, 35, 867–874.
- Karsak, E.E., Kuzgunkaya, O. (2002). A fuzzy multiple objective programming approach for the selection of a flexible manufacturing system. *International Journal of Production Economics*, 79, 101–111.
- Karsak, E.E., Tolga, E. (2001). Fuzzy multi-criteria decision-making procedure for evaluating advanced manufacturing system investments. *International Journal of Production Economics*, 69, 49–64.
- Khouja, M. (1995). The use of data envelopment analysis for technology selection. *Computers & Industrial Engineering*, 28, 123–132.
- Kulak, O., Kahraman, C. (2005). Fuzzy multi-attribute selection among transportation companies using axiomatic design and analytic hierarchy process. *Information Sciences*, 170(2), 191–210.
- Lee, S. (1972). *Linear Programming for Decision Analysis*. Auerbach Publishers, Philadelphia, PA.
- Lin, S.S., Zhang, C., Wang, H.P. (1995). On mixed-discrete nonlinear optimization problems: a comparative study. *Engineering Optimization*, 23, 287–300.
- Liu, T.S. (2008). A fuzzy DEA/AR approach to the selection of flexible manufacturing systems. *Computers & Industrial Engineering*, 54, 66–76.
- Luong, L.H. (1998). A decision support system for the selection of computer-integrated manufacturing technologies. *Robotics and Computer-Integrated Manufacturing*, 14(1), 45–53.
- Man, K., Tang, K., Kwong, S. (1999). *Genetic Algorithms: Concepts and Designs*, second ed. Springer-Verlag, Berlin.
- Mandal, U.K., Sarkar, B. (2012). Selection of best intelligent manufacturing system (IMS) under fuzzy MOORA conflicting MCDM environment. *International Journal of Emerging Technology and Advanced Engineering*, 2(9), 301–310.
- Moore, R.E. (1966). *Interval Analysis*. Prentice-Hall, Englewood Cliffs, NJ.
- Ragavan, P., Punniyamoorthy, M. (2003). A strategic decision model for the justification of technology selection. *The International Journal of Advanced Manufacturing Technology*, 21(1), 72–78.
- Rao, R.V. (2006). A decision-making framework model for evaluating flexible manufacturing systems using digraph and matrix methods. *International Journal of Advanced Manufacturing Technology*, 30, 1101–1110.
- Rao, R.V. (2007). *Decision Making in the Manufacturing Environment: Using Graph Theory and Fuzzy Multiple Attribute Decision Making Methods*. Springer Science & Business Media.
- Rao, R.V. (2013). A combinatorial mathematics-based decision making method. In: *Decision Making in Manufacturing Environment Using Graph Theory and Fuzzy Multiple Attribute Decision Making Methods*. Springer, London, pp. 193–203.
- Rao, R.V., Parnichkun, M. (2009). Flexible manufacturing system selection using a combinatorial mathematics-based decision-making method. *International Journal of Production Research*, 47, 6981–6998.
- Saidi Mehrabad, M., Anvari, M. (2009). Provident decision making by considering dynamic and fuzzy environment for FMS evaluation. *International Journal of Production Research*, 48, 4555–4584.
- Samvedi, A., Jain, V., Chan, F.T.S. (2011). An integrated approach for machine tool selection using fuzzy analytical hierarchy process and grey relational analysis. *International Journal of Production Research*, 50, 3211–3221.
- Sener, Z., Karsak, E.E. (2007). A decision model for advanced manufacturing technology selection using fuzzy regression and fuzzy optimization. In: *IEEE Proceedings*, Istanbul, Turkey, pp. 565–569.
- Shang, J., Sueyoshi, T. (1995). A unified framework for the selection of a flexible manufacturing system. *European Journal of Operation Research*, 85, 297–315.
- Singh, R., Singhal, S., Sharma, P. (2016). Application of AHP in the analysis of flexible manufacturing system. *Journal of Industrial and Intelligent Information*, 4(1), 15–20.
- Stam, A., Kuula, M. (1991). Selecting a flexible manufacturing system using multiple criteria analysis. *International Journal of Production Research*, 29, 803–820.

- Tao, F., Cheng, Y., Zhang, L., Nee, A.Y.C. (2015). Advanced manufacturing systems: socialization characteristics and trends. *Journal of Intelligent Manufacturing*, 1–16. doi:10.1007/s10845-015-1042-8.
- Tseng, M.L. (2008). A causal and effect decision making model of service quality expectation using grey-fuzzy DEMATEL approach. *Expert Systems with Applications*, 36, 7738–7748.
- Wu, Q., Zhou, W., Li, S., Wu, X. (2005). Application of grey numerical model to groundwater resource evaluation. *Environmental Geology*, 47, 991–999.

H. Hosseini-Nasab is a Professor at University of Yazd. He received his PhD at University of Bath, UK in 2001. He has worked on manufacturing systems and cost management for many years.

M. Dehghanbaghi is a PhD candidate of industrial engineering at Yazd University in Iran. She holds her Master degree of industrial engineering at University of Tehran. Her research interests focus on decision making techniques, performance measurement, reverse supply chain and expert systems.

J. Antucheviciene is a Professor at the Department of Construction Technology and Management at Vilnius Gediminas Technical University, Lithuania. She received a PhD in 2005. Research interests include multiple criteria analysis, decision-making theories and decision support systems, sustainable development, construction management and investment.

E. Mehranbarfar is a researcher. He received MBA from Amir Kabir University of Technology in 2013. His main research interests include strategic management, decision making & economics.

Integruotas daugiapakopis metodas lanksčios gamybos sistemų deriniams parinkti

Hasan HOSSEINI-NASAB, Maryam DEHGHANBAGHI, Jurgita ANTUCHEVICIENE, Ehsan MEHRABANFAR

Didelės pasaulinės konkurencijos sąlygomis gaminių kaina, kokybė ir patenkinti klientai yra ypač reikšmingi dalykai. Lanksčios gamybos sistemos turi didelį potencialą gaminti ekonomiškai efektyvius, klientų poreikius atitinkančius ir aplinką tausojančius produktus. Kita vertus, nors šios sistemos ir yra lanksčios, lankstumą lydi didesnės materialinės ir laiko sąnaudos. Taigi tinkamos lanksčios gamybos sistemos pasirinkimas yra daug tyrimų reikalaujanti sritis. Šių sistemų vertinimas ir atranka tampa dar sudėtingesni, kai susiduriama su derinių, sudarytų iš kelių sistemų, pasirinkimo problema. Todėl šiame straipsnyje siūlomas integruotas sprendimų priėmimo metodas, ieškant tinkamiausios lanksčių gamybos sistemų kombinacijos. Kadangi kiekviena lanksčios gamybos sistema gali turėti keletą alternatyvų, yra daug galimų būdų išspręsti šią problemą. Pirmiausia yra nustatomi objektyvūs ir subjektyvūs pasirinkimo kriterijai. Tada Pilkųjų sistemų teorija yra taikoma nevisai ir netiksliai informacijai, susijusiai su subjektyviais kriterijais, aprašyti. Objektyvūs duomenys yra gaunami imitaciniu modeliavimu. Problemai formuluoti ir tikslams priskirti prioritetus taikomas tikslinio programavimo modelis. Galiausiai sistemų derinio parinkimo problemai spręsti taikomas genetiniu algoritmu pagrįstas modelis. Taigi straipsnyje siūlomas integruotas modelis palengvina sudėtingos problemos sprendimų priėmimą ir padeda nustatyti tinkamiausią lanksčių gamybos sistemų derinį.