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Full Length Research Paper

A performance measurement system under activity based costing for advanced manufacturing systems by an integrated fuzzy AHP-fuzzy TOPSIS approach

A. Mohammadzadeh[1], A. Rezazadeh[2], S. Nazari-Shirkouhi[3], M. Ghadamyari[1] and M. R. Dalvand[4]*

[1]Faculty of Management and Accounting, Qazvin Branch, Islamic Azad University, Qazvin, Iran.
[2]Department of Technical Engineering, Ahar Branch, Islamic Azad University, Ahar, Iran.
[3]Roudbar Branch, Islamic Azad University, Roudbar, Iran.
[4]Zahedshahr Branch, Islamic Azad University, Zahedshahr, Iran.

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Nowadays, most of manufacturing firms try to reduce manufacturing response time, improve quality and decrease the costs by investing on advance manufacturing systems (AMSs) as the critical and vital strategic tools. Although the investment and successful implementation of AMSs has many potential advantages and benefits for manufacturing firms, a performance measurement system of manufacturing firms is a very complex task due to the many variables involved in measuring performance of advanced manufacturing systems. During the last decade, measuring performance of AMSs has emerged as a major issue for manufacturing firms. As traditional performance measurement systems are criticized, the aim of this paper is presenting an integrated fuzzy group decision making approach based on fuzzy analytical hierarchy process (fuzzy AHP) and fuzzy technique for order performance by similarity to ideal solution (fuzzy TOPSIS) to measure the performance of AMSs under activity based costing (ABC) systems. Using fuzzy theory for measuring the performance of AMSs in manufacturing firms can reduce ambiguities and uncertainties that are inherent in the performance measurement procedure. Finally, to illustrate the applicability and feasibility of the proposed approach an experiment with six manufacturers is considered and results are provided.

Key words: Fuzzy set, advanced manufacturing systems, activity based costing, fuzzy AHP, fuzzy TOPSIS.

INTRODUCTION

In today's competitive environment, most of manufacturing firms are attempting for meeting demand, increasing quality, decreasing costs, and delivery rate. Factors such as flexibility, quality, time and innovativeness together with cost determine competitive advantage and define the competition pattern (Swink and Nair, 2007; Dangayach and Deshmukh, 2005). According to Brown (2000) if a willingness of the firm is to remain in business, there is no other option whether to invest in technology or not. The firm can merely choose the type and extend of process technological investment. To overcome this challenging, the willingness of most companies is to adopt and invest in an AMS that emphasizes quality, delivery, and flexibility to meet customers' requirements simultaneously (Boyle, 2006; Kim et al., 1997). The advanced manufacturing systems are computer-oriented technologies applied in manufacturing, design, etc. According to Beaumont et al. (2002), advanced manufacturing technology involves computer-aided design (CAD), computer numerical control machines, direct numerical control machines, robotics, flexible manufacturing system (FMS), automated storage and retrieval system (ASRS), automated material handling systems (MHS), automated guided vehicles, bar coding, rapid prototyping, material requirement planning, statistical process control,

*Corresponding author. E-mail: mreza.dalvand@gmail.com.

manufacturing resource planning (MRP), enterprise resource planning (ERP), ABC, and office automation. Evaluating AMSs often include multiple, conflicting objectives, tangible and intangible factors. Applications of traditional cost accounting and financially oriented traditional performance measurement methods do not fully account for the benefits arising from intangible factors of AMS evaluation (Kahraman et al., 2000). Performance indicators for evaluating performance of manufacturing systems can improve manufacturing competitive success.

To overcome disadvantages of traditional performance measurement and to achieve competitive goals, selection of a range of performance indicators appropriate for manufacturers should be made based on a company's strategic intentions that suit competitive environments and the nature of business (Yang et al., 2009). Udo and Ehie (1996) prepared a common overview of tangibles and intangible factors that should be taken into account in the evaluation process. Raafat (2002) presented a comprehensive review on justification of AMS using 231 articles. Beskese et al. (2004) gave a model for quantification of flexibility in AMSs based on fuzzy logic. A study of classification approaches to justify AMSs is by Kolli et al. (1992). They classified existing methods into two major methods: single-criterion and multi-criteria under deterministic and nondeterministic environment. Park and Kim (1995) employed the activity-based costing concept, to make an investment decision among several alternatives of advanced manufacturing technology (AMT). Many research have been focused on various models of evaluation and selection of AMSs from simple financial analysis methods, such as Net Present Value (NPV) method, Return on Investment (ROI), and Internal Rate of return (IRR) (for example, Sullivan et al., 2003), to more complex multi-criteria mathematical programming methods. However, the need for a structured methodology for evaluation AMSs is felt. The insufficiency of traditional financial analysis and appraising measures lies on their non-stochastic nature. The conventional financial analysis methods do not appear to be suitable on their own for the evaluation of advanced manufacturing technologies investments due to the nonmonetary impacts posed by the manufacturing System (Duran and Aguilo, 2008). Anyway, financial analysis (NPV, ROI, IRR, and etc.) can lead to incorrect results in most of real-world applications.

Since intangible factors cannot be obtained in quantitative terms, many articles have concentrated on merging the qualitative and quantitative aspects for evaluating the advantages and benefits of AMSs. Wabalickis (1988) presented an overview of the potential benefits derived from a FMS implementation based on the AHP. Stam and Kuula (1991) developed a two-phase decision procedure that uses the AHP method and multi-objective mathematical programming to select an FMS. Although AHP is variously used in selection problems of FMS, but it suffers from a number of disadvantages. Boucher et al. (1997) argued that AHP is often criticized for the way the criteria weights are elicited, rank reversal problem, inappropriateness of the crisp ratio representation, and problems faced in the comparison process when the number of criteria and/or the number of alternatives increase. In addition, Bayazit (2005) presented an AHP approach for selecting a FMS. Rezaie et al. (2009b) and Rezaie et al. (2010) proposed a method for evaluating the FMS based on a model incorporating two decision models namely "DEA" and "AHP. Rehman and Subash Babu (2009) also used the AHP tool to alternative reconfigurable manufacturing systems. Recently, fuzzy multi criteria decision-making (MCDM) techniques are extensively applied to evaluate benefits of AMSs. Perego and Rangone (1998) gave a reference framework for the application of three major categories of fuzzy MADM approach in the assessment and selection of AMS. Karsak and Tolga (2001) presented a fuzzy MCDM approach to select the most suitable AMS alternative from a set of mutually exclusive alternatives regarding both economic evaluation criterion and strategic criteria such as flexibility, quality improvement. Chuu (2009) developed a fuzzy multiple attribute decision-making applied in the group decision-making to improve advanced manufacturing technology selection process.

They developed a new fusion method of fuzzy information to managing information assessed in different linguistic scales (multi-granularity linguistic term sets) and numerical scales. Abdel-Kader and Dugdale (2001) proposed a fuzzy MADM approach for the evaluation of investments in advanced manufacturing technology. They applied mathematics of the AHP and fuzzy set theory to integrate the two major dimensions of financial and non-financial factors. Chan et al. (2006) proposed an integrated decision support system, which incorporates different justification methods (for example, strategic, economic and analytic evaluations) for assessing tangible benefits, like cost, and intangible benefits, like quality, of different alternatives by a fuzzy MCDM method. To handle the complexity of the current industrial context, new control strategies devised for continuous improvement, on the one hand, the multi-criteria performance expression aspects, and the modeling of their relationships (Berrah et al., 2004). To achieve this aim, the performance measurement systems (PMSs) which are instruments to support decision-making can be applied. Then, in order to support the decision, the set of performances has to be processed so as to compare the different situations (Berrah et al., 2008). Thus PMSs require by nature the use of MCDM methods (Santos et al., 2002). Recently, many studies have applied new performance measurement systems with respect to the ABC system (Askarany et al., 2010; Banker et al., 2008).

The ABC system was first introduced by Cooper and Kaplan (1988) to clearly define the correlation between

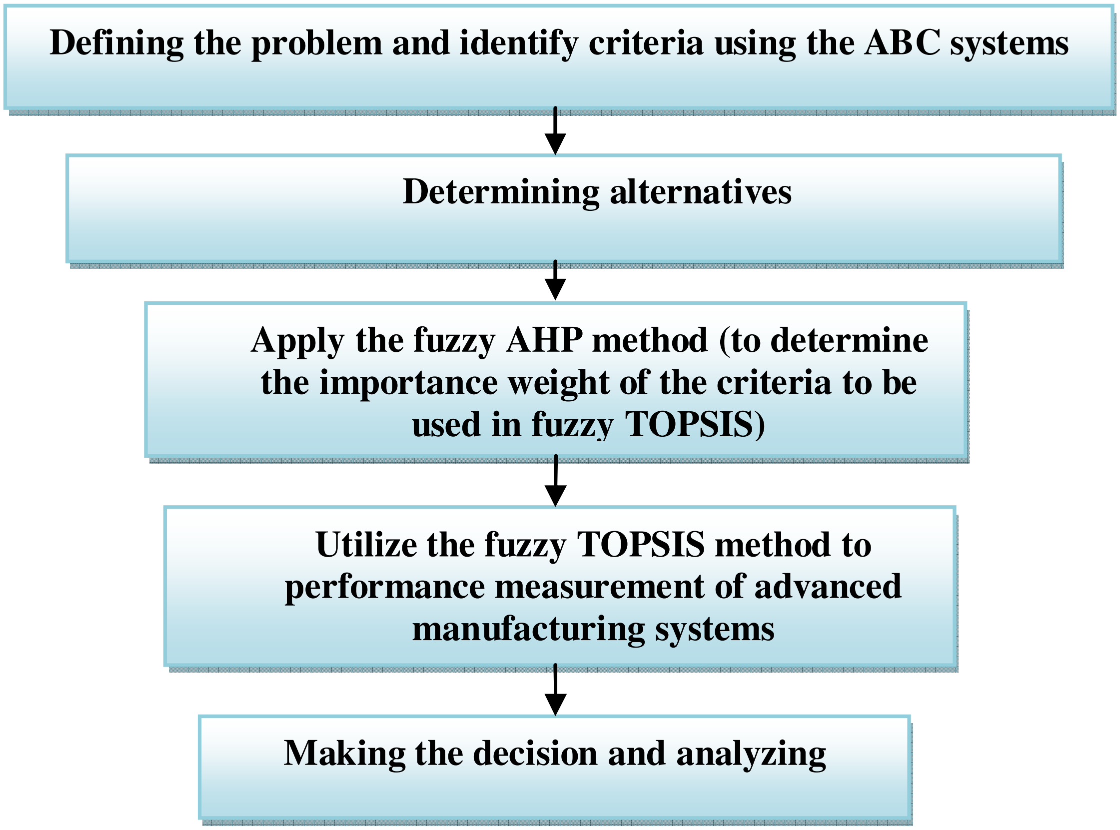

Figure 1. The steps of the proposed methodology in uncertainty environment.

cost drivers and objectives, and consequently rationalize the cost sharing problems. ABC could be useful for companies by supplying clear, accurate and associated cost information in a well-timed and suitable manner and managers can control by activities which derive from costs. Activities can be measured by valuable performance attributes such as quality, flexibility, customers' satisfaction, and cost and the managers often are interested in seeing how effectively activities are performed from the integrated viewpoint instead of separated viewpoint (Kim et al., 1997). In this paper, the principle of ABC systems are used to define and present the major criteria to PMS of advanced manufacturing systems. The fuzzy analytical hierarchy process (fuzzy AHP) is used to analyze the structure of the PMS problem and determine weights of the criteria which are achieved using ABC systems, and fuzzy technique for order performance by similarity to ideal solution (fuzzy TOPSIS) is used for final ranking of advanced manufacturing systems. The distinguishing feature of our study is that, on contrary to similar studies that have used their own selection criteria for evaluating performance of advanced manufacturing systems, the criteria are selected through the ABC systems. Furthermore, experts' judgments are used for determining the relative importance and weight of ranking criteria.

THE PROPOSED METHODOLOGY

In this section, we describe our proposed methodology to performance measurement for advanced manufacturing systems by the fuzzy AHP and fuzzy TOPSIS. In order to measure the performance of the advanced manufacturing systems the following procedure is devised.

1- Defining the problem and identify criteria using the ABC systems.
2- Determining alternatives (firms which should be measured based on their AMSs' performance).
3- Applying the fuzzy AHP method to determine the importance weight of the criteria to be used in fuzzy TOPSIS.
4- Utilizing the fuzzy TOPSIS method to performance measurement of advanced manufacturing systems.
5- Making the decision and analyzing.

A proposed methodology to performance measurement of the advanced manufacturing systems using ABC systems is depicted in Figure 1.

Fuzzy analytical hierarchy process (AHP)

Multi-criteria decision-making is one of the useful approaches for

Table 1. Fuzzy scale used for making pair-wise comparisons (Saaty, 1980).

Fuzzy number	Fuzzy scale	Definition	Explanation
$\tilde{1}$	(1,1,1)	Equal importance	Two activities contribute equally to objective
$\tilde{3}$	(2,3,4)	Weak importance	Experience and judgment slightly favour one activity over another
$\tilde{5}$	(4,5,6)	Essential or strong importance	Experience and judgment strongly favor one activity over another
$\tilde{7}$	(6,7,8)	Demonstrated importance	One activity is strongly favoured and demonstrated in practice
$\tilde{9}$	(8,9,9)	Extreme importance	The evidence favouring one activity over another is of highest possible order of affirmation
$\tilde{x}$	(x-1,x,x+1)	Intermediate values between two adjacent judgments	When compromise is needed
$1/\tilde{x}$	(1/(x+1),1/x,1/(x-1))	Inverse values	

dealing with problems having conflicting objectives. AHP is one of the MCDM method introduced by Saaty (1980). The classical AHP method does not consider uncertainty conditions. Since fuzzy concept is one of the useful tools for explaining uncertainty, the fuzzy AHP method is used for coping with this limitation. the fuzzy AHP method has been applied in various researches for making decision in different fields such as evaluating and selecting of simulation software package (Azadeh et al., 2010), evaluating effective factors of implementing knowledge management (Rezaie et al., 2009a), evaluating risk of information technology projects (Iranmanesh et al., 2008), assigning productive operators' in cellular manufacturing systems (Azadeh et al., 2011), and so on. The fuzzy AHP method is explained in the following.

Converting the expert's opinion to fuzzy scale

In classic AHP, introduced by Saaty (1980), experts explain their opinions using numbers and precise ratios. These explained ratios construct the pair-wise comparison matrix which weight of each factor in the same level is achieved by calculating its eigen values matrix. Roh et al. (2005) believe that this kind of decision making is not precise and it is unpromising. Leung and Cao (2000) believe that it is a consequence of expert's opinions uncertainty. In classical AHP, the expert's opinions are expressed in terms of crisp data whereas opinion cannot be explained by crisp data. Due to the fact that fuzzy concept is more useful for dealing with uncertainty, integrating AHP and fuzzy logic is a suitable method for simulating decision making procedure. Hence, in the step of expert's opinion collection, common linguistic terms are used in the questionnaires. Converting these qualitative terms to quantitative terms is required for analyzing the expert's opinion. The fuzzy scale introduced by (Saaty, 1980) and shown in Table 1 is used for quantifying the expert's opinion.

Integrating the expert's opinion

An Opinion about the relative importance of criteria C_i and C_j can be shown as $\tilde{I}_{ij} = (I_{ij}^l, I_{ij}^m, I_{ij}^u)$, and three parameters of the triangular fuzzy number $\tilde{I}$ are calculated in Equations 1 to 3.

$$I_{ij}^l = \min\{O_{ijk}^l\} \tag{1}$$

$$I_{ij}^m = \sqrt[n]{\prod_1^n O_{ijk}^m} \tag{2}$$

$$I_{ij}^u = \max\{O_{ijk}^u\} \tag{3}$$

Where, O_{ijk}^l, O_{ijk}^m, and O_{ijk}^u are the first, second, and third parameter of the integrated expert's opinion.

Diffuzzifying the expert's opinion

There are various approaches for difuzzifying expert's opinion that a prerequisite of many of them is normal membership function or triangular membership function. In addition, in all of them the expert's opinion uncertainty is ignored. According to this drawback, a special difuzzification method introduced by Liou and Wang (1992), is used for coping with these limitations. If the fuzzy pair-wise comparison matrix $\tilde{F}$ is shown as Equation 4, then converting the fuzzy pair-wise comparison matrix $\tilde{F}$ to crisp pair-wise comparison matrix P is Equation 5.

$$\tilde{F} = [\tilde{f}_{ij}] = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} 1 & \tilde{f}_{12} & \cdots & \tilde{f}_{1n} \\ 1/\tilde{f}_{12} & 1 & \cdots & \tilde{f}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{f}_{1n} & 1/\tilde{f}_{2n} & \cdots & 1 \end{bmatrix} \end{array} \tag{4}$$

$$P = [p_{ij}] = \begin{cases} \beta((f_{ij}^m - f_{ij}^l)\alpha + f_{ij}^l) + (1-\beta)(f_{ij}^u - (f_{ij}^u - f_{ij}^m)\alpha) & ; 0 \le \alpha, \beta \le 1 \quad i \le j \\ 1/p_{ij}, \ 0 \le \alpha, \beta \le 1 & i > j \end{cases} \tag{5}$$

Where α and β are preference and risk tolerance of the decision

Table 2. Random index for various values of n.

n	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48

Table 3. Linguistic variables for the ratings.

Linguistic scales	Corresponding triangular fuzzy number
Very poor (VP)	(0,0,1)
Poor (P)	(0,1,3)
Medium poor (MP)	(1,3,5)
Fair (F)	(3,5,7)
Medium good (MG)	(5,7,9)
Good (G)	(7,9,10)
Very good (VG)	(9,10,10)

maker, respectively. Finally the crisp pair-wise comparison matrix $\tilde{P}$ is Equation 6.

$$P = [p_{ij}] = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} 1 & p_{12} & \cdots & p_{1n} \\ 1/p_{12} & 1 & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/p_{1n} & 1/p_{2n} & \cdots & 1 \end{bmatrix} \end{array} \tag{6}$$

The β is pessimism indicator that is, if $\beta = 0$ then we can see the certainty of accuracy in pair-wise comparison is as low as possible. In this study both α and β are considered equal to 0.5.

Calculating the consistency rate

If we have $\begin{cases} p_{ij} = 1/p_{ij} & i \neq j \\ p_{ii} = 1 & i = j \end{cases}$ in crisp pair-wise comparison matrix, then consistency rate of the decision is calculated by Equation 7.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{7}$$

Where, *n* is the number of criteria and $\lambda_{\max}$ is the largest value in eigen value matrix. Consistency index (CI) indicates whether a decision maker provides consistent values (comparisons) in a set of evaluation. The final inconsistency in the pair-wise comparisons is solved using consistency ratio $CR = \frac{CI}{RI}$, where *RI* is the random index. The *RI* is obtained by averaging the *CI* of a randomly generated pair-wise matrix (Saaty, 1980). Table 2 shows some value of *RI* in terms of *n*.

Calculating the weight of factors

The weights of factors are calculated by solving Equations 8 and 9 simultaneously.

$$\begin{cases} (P - \lambda_{\max})W = 0 & (8) \\ \sum W = 1 & (9) \end{cases}$$

Where, P is the crisp pair-wise comparison matrix, $\lambda_{\max}$ is the largest value in eigen-value matrix, and W is the weight matrix.

Fuzzy technique for order performance by similarity to ideal solution (TOPSIS)

In this section, the fuzzy TOPSIS method is presented. The mathematics concept is taken from Wang and Chang (2007) and Chen (2000). Steps of fuzzy TOPSIS are as follow:

The linguistic variables which are used in this paper are expressed in Table 3. The average rating of alternatives or each member of fuzzy decision matrix can be calculated using Equation (10).

$$\tilde{x}_{ij} = \frac{1}{k}(\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + \ldots + \tilde{x}_{ij}^k) \ \ and \ \ \tilde{x}_{ij}^k = (a^k{}_{ij}, b^k{}_{ij}, c^k{}_{ij}) \tag{10}$$

After obtaining average matrix of alternatives ratings, a linear scale transformation is used to transform the various criteria scales into a comparable scale. The normalized fuzzy decision matrix denoted by $\tilde{R}$ can be shown as follow:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n,} \ i = 1, 2, \ldots, m \ \ ; \ \ j = 1, 2, \ldots, n.$$

Normalization process of fuzzy decision matrix is performed by following linear scale transformation. B and C are the set of benefit and cost criteria, respectively:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c^+_j}, \frac{b_{ij}}{c^+_j}, \frac{c_{ij}}{c^+_j} \right) \quad c^+_j = \max_i c_{ij} \;\; j \in B \tag{11}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right) \quad a_j^- = \min_i a_{ij} \;\; j \in C \tag{12}$$

After using Equation (11 to 12), the normalized fuzzy decision matrix $\tilde{r}_{ij}$ still has triangular fuzzy numbers. With respect to different importance of each criterion from the fuzzy AHP, the weighted normalized fuzzy decision matrix can construct as following matrix $\tilde{V}$:

$$\tilde{V} = [\tilde{v}_{ij}]_{n \times n}, \; i = 1,2,...,m; j = 1,2,...,n \;\; , \;\; \tilde{v}_{ij} = w_j . \tilde{r}_{ij} \tag{13}$$

w_j is a weight of each criterion from the fuzzy AHP. The fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS) can be calculated through following equations:

$$A^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, ..., \tilde{v}_n^+ \right) \quad , \quad A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, ..., \tilde{v}_n^- \right) \tag{14}$$

Distance of each alternative with fuzzy positive ideal solution and fuzzy negative ideal solution are computed as follows:

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad i=1,2,...,m; \; j=1,2,...,n$$

(15)

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i=1,2,...,m; \; j=1,2,...,n$$

Where, $d(\tilde{v}_a, \tilde{v}_b)$, d_i^+, and d_i^- represent the distance between two fuzzy numbers, distance of alternative i from ideal solution, and distance of alternative i form negative ideal solution. The closeness coefficient (CC_i) is defined to determine the ranking order of all alternatives once the d^+_i and d^-_i of each alternative have been calculated. Similarities to ideal solution can be calculated by the following equation:

$$CC_i = \frac{d^-_i}{d^+_i + d^-_i}, i = 1,2,...,m. \tag{16}$$

If alternative A_i is closer to FPIS (A^+) and being far from FNIS (A^-), then CC_i approaches to 1. Therefore, according to the closeness coefficient, we can calculate the ranking order of all alternatives and select the best set of feasible alternatives.

EXPERIMENT AND RESULTS

The traditional performance measurement systems are locate in a particular place accounting information, standards, and represent financial data. Kaplan (1991) emphasized that the traditional performance measurement systems have limitation and disadvantages in several aspects: Relevant information is received too late for corrective actions to be taken, the information is reported at too aggregated level, the information is distorted by unnecessary allocations, and excessive attention is devoted to financial measures at the expense of operating measures. The performance measurement system can be defined as the set of criteria applied to quantify both the efficiency and effectiveness of actions. An effective manufacturing performance measurement system should be both explicit and objective, and provide a means for continuously improving a system (Yang et al., 2009). Since overhead costs in general occupy higher percentage of the manufacturing cost rather than direct costs in an AMS, a PMS introduced in this paper tries control the manufacturing cost through improved performance of the activity by applying ABC systems.

The principle of ABC systems attempt to meet the requirement of the new performance measurement systems (Yang et al., 2009). This means that ABC systems allot the costs of an organization's activities more perfectly to its products and product lines. ABC systems are designed by first identifying the activities performed by each support and operating department and then computing the unit costs of performing these activities (Glad et al., 1996). Hence, to develop a PMS, it is required to define performance measures/performance criteria of the activity. In this study, the performance criteria of Kim et al. (1997) have been adapted. Table 4 contains the list of criteria which are adapted from Kim et al. (1997). It also contains brief explanation for each criterion. In this paper, we have selected six manufacturers (manufacturer A, B, C, D, E, and F). The decision makers can change, add or omit the alternatives (along with its competitors) with respect to the context for which they are going to use AMSs for producing same products. The hierarchical structure of the problem is shown in Figure 2. Therefore, by using Equations (8 and 9) the importance weight of the criteria (W) to be used in fuzzy TOPSIS will be as Table 6. $C.I.$ and $C.R.$ can be calculated using Equation (7) and are 0.0318 and 0.0358. After establishing the hierarchical structure for Measuring Performance of AMS, first fuzzy AHP method is applied to determine the importance weight of the criteria to be used in fuzzy TOPSIS. According to Equation (1 to 3), based on Table 5, the fuzzy decision matrix for the considered criteria to performance measurement of AMSs under ABC system is attained from a verbal

Table 4. List of criteria for measuring performance of amss under activity based costing.

Criteria	Explanation
Quality of an activity	Quality of an activity can be defined quality as fitness for use (Juran and Gyrna, 1980). In AMSs, fitness for use is capability to perform the operations with low waste, high productivity, and minimal downtime. In general, the quality of an activity can be measured by the quality of available resources associated with activity. The higher percentage of defective products and rework lead to the lower quality of the activity.
Completion time of an activity	Criterion of the completion time of an activity is indirect criterion of cost, quality, and internal or external customer service. Shorter time of an activity to perform means that lesser the resources it requires and firm can rapidly react to extensively changes in customers' requirements as a competitive advantage.
Setup time of an activity	Setup time is the time to make ready the equipment to produce different product/parts. Reduction in setup time is desired and leads to reduced inventory level, improved quality, and faster customer response and may have a positive impact on flexibility and cost of manufacturing.
Efficiency of an activity	The efficiency of an activity can be defined as the relationship between the level of resource applied and what has been achieved. In general, when a company intend to investigate its activities, it is required to exploit the efficiency of an activity concept in order to visualize and quantify cost behavior

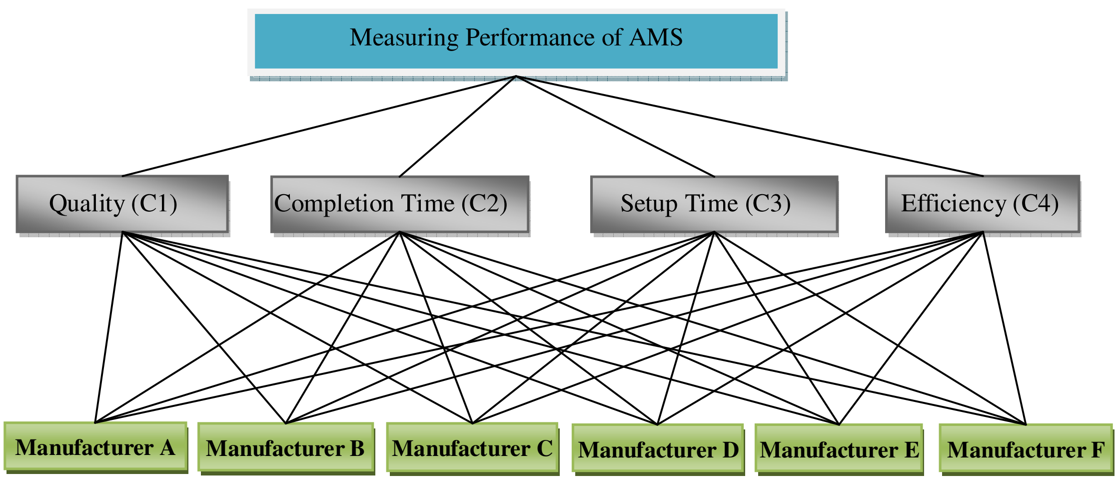

Figure 2. The hierarchical structure for measuring performance of AMSs under activity based costing.

Table 5. Aggregated fuzzy pair-wise comparison of criteria for measuring performance of AMSs.

	C_1	C_2	C_3	C_4
C_1	(1,1,1)	(0.2,1.785,7)	(1,3.347,8)	(0.167,1.842,6)
C_2	-	(1,1,1)	(0.25,4.145,8)	(0.125,1.123,4)
C_3	-	-	(1,1,1)	(0.167,0.673,83)
C_4	-	-	-	(1,1,1)

questionnaire filled by fourteen different experts and then converted to fuzzy numbers based on Saaty's scale (1980).

In this paper, α and β are considered equal to 0.5.

Selecting $\alpha = 0.5$ indicates that environmental uncertainty is steady; additionally $\beta = 0.5$ indicates that a future attitude would be fair. After calculating the weight of criteria using fuzzy AHP, here, fuzzy TOPSIS method

Table 6. The final weight of criteria for measuring performance of AMSs.

	C_1	C_2	C_3	C_4
Weight	0.4755	0.2703	0.1098	0.1445

Table 7. The fuzzy decision matrix.

	C1			C2			C3			C4		
Manufacturer A	5.76	7.86	9.23	3.12	4.45	5.36	1.45	2.24	3.12	5.87	7.98	9.45
Manufacturer B	4.75	6.75	8.55	2.12	3.84	5.43	6.56	8.12	9.23	6.1	8.18	9.03
Manufacturer C	1.55	3.35	5.35	1.82	2.44	3.56	6.65	8.62	9.1	6.05	8.05	8.85
Manufacturer D	3.47	5.47	7.26	3.45	4.83	6.47	6.35	8.35	8.85	6.15	8.15	8.85
Manufacturer E	2.91	4.5	6.78	5.05	5.03	8.25	4.45	6.78	8.94	2.56	3.45	5.67
Manufacturer F	3.50	5.57	7.13	2.65	4.41	6.29	2.29	4.06	5.94	5.24	7.24	8.29

Table 8. The normalized fuzzy decision matrix.

	C1			C2			C3			C4		
Manufacturer A	0.62	0.85	1.00	0.34	0.41	0.58	0.46	0.65	1.00	0.62	0.84	1.00
Manufacturer B	0.51	0.73	0.93	0.34	0.47	0.86	0.16	0.18	0.22	0.65	0.87	0.96
Manufacturer C	0.17	0.36	0.58	0.51	0.75	1.00	0.16	0.17	0.22	0.64	0.85	0.94
Manufacturer D	0.38	0.59	0.79	0.28	0.38	0.53	0.16	0.17	0.23	0.65	0.86	0.94
Manufacturer E	0.32	0.49	0.73	0.22	0.36	0.36	0.16	0.21	0.33	0.27	0.37	0.60
Manufacturer F	0.38	0.60	0.77	0.29	0.41	0.69	0.24	0.36	0.63	0.55	0.77	0.88

Table 9. The weighted normalized fuzzy decision matrix.

	C1			C2			C3			C4		
Manufacturer A	0.297	0.405	0.476	0.092	0.111	0.158	0.051	0.071	0.110	0.090	0.122	0.145
Manufacturer B	0.245	0.348	0.440	0.091	0.128	0.232	0.017	0.020	0.024	0.093	0.125	0.138
Manufacturer C	0.080	0.173	0.276	0.138	0.202	0.270	0.017	0.018	0.024	0.093	0.123	0.135
Manufacturer D	0.179	0.282	0.374	0.076	0.102	0.143	0.018	0.019	0.025	0.094	0.125	0.135
Manufacturer E	0.150	0.232	0.349	0.060	0.098	0.097	0.018	0.023	0.036	0.039	0.053	0.087
Manufacturer F	0.180	0.287	0.367	0.078	0.112	0.186	0.027	0.039	0.069	0.080	0.111	0.127

can be applied for the performance measurement of manufacturers which use AMS with respect to four criteria (quality of an activity, completion time of an activity, setup time of an activity, efficiency of an activity). Based on Table 3 and Equation 10, the fuzzy decision matrix is constructed and is shown in Table 7. The normalized fuzzy decision matrix $\tilde{R}$, by use of a linear scale transformation in Equations (11 to 12) is shown in Table 8. Note that C2 and C3 belong to cost criteria. By use of results in Table 8 and with respect to different importance of each criterion from fuzzy AHP in Table 6, the weighted normalized fuzzy decision matrix is constructed and shown in Table 9. Figure 3 shows the comparison of the performance measurement of six manufacturers which use AMS. The *FPIS* A^+ and *FNIS* A^- are defined as Equation (14) in which the v_j^+ and v_j^- are the fuzzy numbers in Table 9. The distance of each manufacturer from *FPIS* and *FNIS* are shown in Tables 10 and 11. d_i^+, d_i^-, and CC_i of six manufacturers are calculated using Equation (15 to 16) and are shown in Table 12.

The final CC_i of the manufacturers are as follows: 0.8113 for manufacturer A, 0.6464 for B, 0.3933 for C, 0.4037 for D, 0.1616 for r E, and 0.4909 for F. According

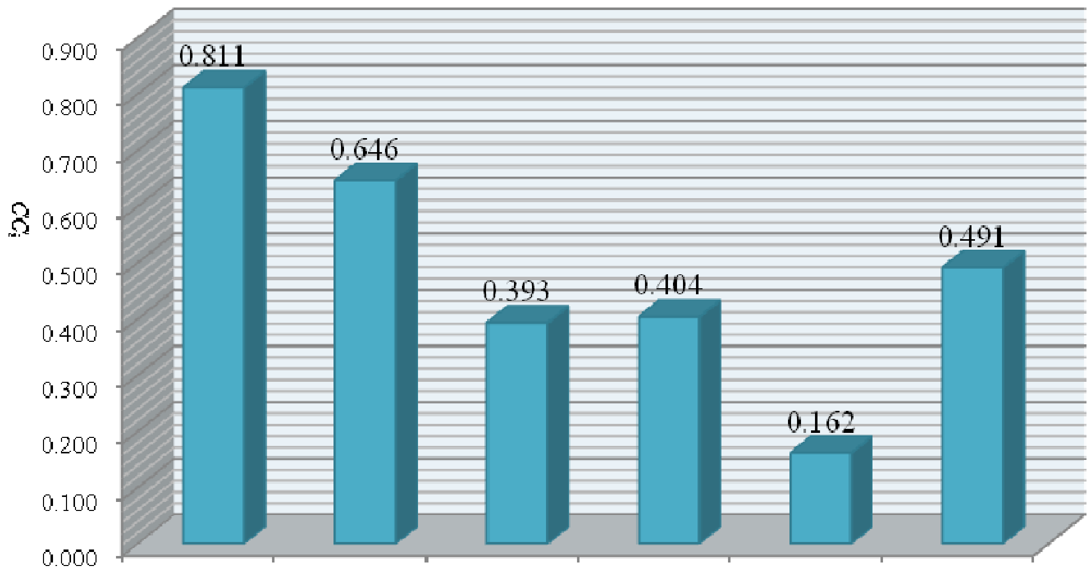

Figure 3. Comparison of performance of AMSs in six manufacturers regarding the closeness coefficients.

Table 10. Distances between Manufacturer (i=A, B, C, D, E and F) and A+ with respect to each criterion.

	C1	C2	C3	C4
d(Manufacturer A, A^+)	0.0000	0.0878	0.0000	0.000
d(Manufacturer B, A^+)	0.0490	0.0552	0.0608	0.005
d(Manufacturer C, A^+)	0.2168	0.0000	0.0613	0.006
d(Manufacturer D, A^+)	0.1144	0.1002	0.0605	0.006
d(Manufacturer E, A^+)	0.1499	0.1250	0.0543	0.060
d(Manufacturer F, A^+)	0.1144	0.0793	0.0328	0.013

Table 11. Distances between manufacturer (i=A, B, C, D, E and F) and A– with respect to each criterion.

	C1	C2	C3	C4
d(Manufacturer A, A^-)	0.2168	0.0401	0.0608	0.0597
d(Manufacturer B, A^-)	0.1684	0.0817	0.0000	0.0600
d(Manufacturer C, A^-)	0.0000	0.1250	0.0007	0.0582
d(Manufacturer D, A^-)	0.1025	0.0278	0.0007	0.0593
d(Manufacturer E, A^-)	0.0679	0.0000	0.0070	0.0000
d(Manufacturer F, A^-)	0.1025	0.0528	0.0289	0.0470

to the obtained results, the manufacturer A has the highest weight and its performance is ranked first position among other manufacturers according to the experts' judgment. Manufacturer A has a good potential capability of being a reference for other manufacturers in one or more performance criteria. Therefore, manufacturers' performance under ABC system for benchmarking is in the following order: Manufacturer A, B, F, D, C, and E. Manufacturer *A* has the closest distance from "quality" (C1), "setup time" (C3), and "efficiency" (C4) and manufacturer *C* from "completion time" (C2). These means that manufacturer *A* is better than the other

Table 12. The distances, closeness coefficients and final ranking of manufacturers.

	d_i^+	d_i^-	CC_i	Final rank
Manufacturer A	0.0878	0.3775	0.8113	1
Manufacturer B	0.1696	0.31	0.6464	2
Manufacturer C	0.2836	0.1838	0.3933	5
Manufacturer D	0.2811	0.1903	0.4037	4
Manufacturer E	0.3889	0.075	0.1616	6
Manufacturer F	0.2398	0.2312	0.4909	3

manufacturers in criteria (quality, setup time, and efficiency) and manufacturer *C* is better than the other manufacturers in criterion completion time (with regarding closest distance). Meanwhile, manufacturer *A* has the farthest distance from "quality" (C1), "setup time" (C3); manufacturer *B* from "efficiency" (C4); and manufacturer *C* from "completion time" (C2). These means manufacturer *A* is better than the other manufacturers in criteria (quality and setup time), manufacturer *B* in criterion (efficiency), and manufacturer *C* is better than the other manufacturers in criterion completion time (with regarding farthest distance).

CONCLUSION

In this paper, an integrated fuzzy multi criteria decision making approach based on Fuzzy AHP and fuzzy TOPSIS for measuring the performance of advanced manufacturing systems in manufacturing firms is proposed for those who work in the field of manufacturing system. Using fuzzy theory for AHP to determine the weight of criteria of fuzzy TOPSIS can reduce ambiguities and uncertainties that are inherent for performance measurement. The proposed methodology uses triangular fuzzy numbers for fuzzy AHP, for values of the criteria used to fuzzy TOPSIS. Using linguistic variables and experts' judgments makes the measurement process for making decision more realistic and reliable. Finally, we suggest that administrators, experts or decision makers of manufacturing firms in related advanced manufacturing systems or performance measurement systems based activity based costing can use our approach to make a decision about performance measurement for their AMSs.

The manufacturing firm management can use proposed approach to enhance effectiveness and/or efficiency of its decision making if there exists a need in case of decision problem in fuzzy environment includes multiple objectives, multiple and conflicting criteria, sub criteria and aims at measuring the performance of AMSs. This makes proposed approach as a decision support method which attracts the attention of managers of performance measurement based activity based costing. For future research, other decision making and ranking methods in fuzzy environment for measuring the performance of AMSs can be used. Also, the comparison of the results of these methods with the proposed methods is suggested. Additionally, the various weight calculation methods for fuzzy TOPSIS such as fuzzy Entropy method, weighted least square method, and fuzzy linear programming for multi dimensions of analysis preference (LINMAP) method can be applied. These methods have been extended in the fuzzy environment and can be used for the comparison of the results. As another direction for future research, more criteria and alternatives can be considered.

Abbreviations: AMSs, Advance manufacturing systems; **AHP,** analytical hierarchy process; **TOPSIS,** technique for order performance by similarity to ideal solution; **ABC,** activity based costing; **CAD,** computer-aided design; **FMS,** flexible manufacturing system; **ASRS,** automated storage and retrieval system; **MHS,** material handling systems; **MRP,** manufacturing resource planning; **ERP,** enterprise resource planning; **AMT,** advanced manufacturing technology; **NPV,** net present value; **ROI,** return on investment; **IRR,** internal rate of return; **DEA,** data envelopment analysis; **MCDM,** multi criteria decision-making; **PMSs,** performance measurement systems; **CI,** consistency index; **FPIS,** fuzzy positive-ideal solution; **FNIS,** fuzzy negative-ideal solution; **CC,** closeness coefficient ; **LINMAP,** linear programming for multi dimensions of analysis preference.

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