

Forecasting the Success of Implementing Sensors Advanced Manufacturing Technology

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Abstract: This paper is presented fuzzy preference relations approach to forecast the success of implementing sensors advanced manufacturing technology (AMT). In the manufacturing environment, performance measurement is based on different quantitative and qualitative factors. This study proposes an analytic hierarchical prediction model based on fuzzy preference relations to help the organizations become aware of the essential factors affecting the AMT implementation, forecasting the chance of successful implementing sensors AMT, as well as identifying the actions necessary before implementing sensors AMT. Then predicted success/failure values are obtained to enable organizations to decide whether to initiate sensors AMT, inhibit adoption or take remedial actions to increase the possibility of successful sensors AMT initiatives. This proposed approach is demonstrated with a real case study involving six influential factors assessed by nine evaluators solicited from a semiconductor engineering incorporation located in Taiwan. Copyright © 2014 IFSA Publishing, S. L.

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1. Introduction

Several researches in the field of Advanced Manufacturing Technology (AMT) have been undertaken. Orr [1] employed the financial evaluation techniques to plan and implement AMT. Talluri and Yoon [2] utilized the cone-ratio DEA in analyzing the AMT selection process. As is well known, the main objective of AMT implementation ought to help enterprises strengthen competitiveness as much as possible, and minimize the unavoidable elimination in the dynamic market. The success or failure of AMT implementation is closely bound to enterprise survival [3-7]. AMT selection and adoption processes have been extensively studied. Topics that include financial and human factors, productivity, and

coordination of the AMT implementation establish a substantial content of the present research agenda.

The next section discusses the fuzzy preference relation. An analytic hierarchy framework based on the additive reciprocity transitivity for predicting AMT implementation is derived in Section 3. In Section 4, an empirical case of AMT initiative in Taiwan is presented. Finally, conclusions are given in Section 5.

2. Reciprocal Additive Consistent Fuzzy Preference Relation

Herrera-Viedma et al. [8] proposed the consistent fuzzy preference relations for establishing pairwise

comparison preference decision matrices using the so-called reciprocal additive transitivity property. This method not only enables decision makers to express their degree of preference for a set of attributes or alternatives, but also avoids the inconsistency in the decision making process. The following briefly describes some definitions and propositions presented in [9-16]. The basic definitions and propositions below are used throughout this study unless otherwise specified.

2.1. Multiplicative Preference Relation

A multiplicative preference relation A on a set of alternatives X is indicated by a matrix $A \subset X \times X$, $A = (a_{ij})$, a_{ij} is the ratio of the preference degree of alternative x_i over x_j , A is assumed multiplicative reciprocal, that is

$$a_{ij} \cdot a_{ji} = 1, \quad (1)$$

2.2. Additive fuzzy preference relation

Suppose a fuzzy preference relation P on a set of alternatives X is denoted by $P = (p_{ij})$, $p_{ij} = \mu_p(x_i, x_j)$. p_{ij} indicates the ratio of the preference intensity of alternative x_i to that of x_j . If $p_{ij} = \frac{1}{2}$ implies there is no difference between x_i and x_j , $p_{ij} = 1$ indicates x_i is absolutely preferred to x_j , similarly $p_{ij} = 0$ indicates x_j is absolutely preferred to x_i , $p_{ij} > \frac{1}{2}$ indicates that x_i is preferred to x_j ($x_i > x_j$). P is assumed additive reciprocal, that is

$$p_{ij} + p_{ji} = 1, \quad (2)$$

Proposition. Suppose there is a set of alternatives $X = \{x_1, \dots, x_n\}$, which is associated with a multiplicative preference relation $A = (a_{ij})$ with $a_{ij} \in [\frac{1}{9}, 9]$. Then the corresponding reciprocal additive fuzzy preference relation $P = (p_{ij})$ with $p_{ij} \in [0, 1]$ to $A = (a_{ij})$ is defined as follows.

$$p_{ij} = g(a_{ij}) = \frac{1}{2} \cdot (1 + \log_9 a_{ij}), \quad (3)$$

2.3. Additive Transitivity Consistency of Fuzzy Preference Relation

A reciprocal additive fuzzy preference relation $P = (p_{ij})$ is consistent if

$$p_{ij} + p_{jk} + p_{ki} = \frac{3}{2}, \quad (4)$$

2.4. Construct a Consistent Fuzzy Preference Relation

A consistent fuzzy preference relation P' on $X = \{x_1, x_2, \dots, x_n, n \geq 2\}$ from $n-1$ preference values $\{p_{12}, p_{23}, \dots, p_{n-1n}\}$ can be constructed as follow.

- Compute the set of preference values B as

$$B = \{p_{ij}, i < j \wedge p_{ij} \notin \{p_{12}, p_{23}, \dots, p_{n-1n}\}\}$$

$$p_{ji} = \frac{j-i+1}{2} - p_{i+1} - p_{i+1+2} \dots - p_{j-1j}, \quad (5)$$

$$a = \left| \min\{B \cup \{p_{12}, p_{23}, \dots, p_{n-1n}\}\} \right|, \quad (6)$$

$$P = \{p_{12}, p_{23}, \dots, p_{n-1n}\} \cup B \cup \{1 - p_{12}, 1 - p_{23}, \dots, 1 - p_{n-1n}\} \cup \neg B, \quad (7)$$

- The consistent fuzzy preference relation P' is obtained as $P' = f(P)$

$$f: [-a, 1+a] \rightarrow [0, 1], f(x) = \frac{x+a}{1+2a}, \quad (8)$$

3. Framework for Predicting Advanced Manufacturing Technology Implementation

This section comprises four subsections: investigating the influential factors on AMT initiative, determining the priority weights of influential factors, determining the synthetic rating of possible outcomes, and obtaining the priority weights for prediction.

3.1. Investigating the Influential Factors on AMT Implementation

The influential factors are derived through widespread investigation and consultation with several experts, including two professors in information management, one professor in information engineering, three professors in business administration and five experienced AMT project managers. Synthesizing the literature review from [1-4], the opinions of these experts are utilized to yield the six key influential factors used in this study. F1: A committed and informed executive sponsor, F2: An operating sponsor, F3: Think-tank linkage, F4: Alignment of business, organization, and

technological objectives, F5: Integration with the existing system, F6: Natural organizational interfaces to the new system.

3.2. Determining the Priority Weights of Influential Factors

This study provides the evaluators simple linguistic terms quantified on a scale of $[\frac{1}{9}, 9]$ to express their strength of preference among influential factors.

3.2.1. Linguistic Variables

Five linguistic terms are provided for comparing neighboring factors corresponding to a real number (see Table 1), and linguistic variables are simultaneously used to measure the likelihood of success/failure regarding each influential factor (see Table 2).

Table 1. Linguistic terms for weights of influential factors.

Definition	Intensity of importance
Equally important (EQ)	1
Weakly more important (WK)	3
Strongly more important (ST)	5
Very strongly more important (VS)	7
Absolutely more important (AB)	9

Table 2. Linguistic variables for measuring probability of success.

Definition	Intensity of importance
Fair (F)	1
High (H)	3
Very high (VH)	5

3.2.2. Obtaining Priority Weights of Influential Factor

In conventional AHP or Fuzzy AHP, evaluators always provide $\frac{n(n-1)}{2}$ judgments, while consistent fuzzy preference relation presented by Herrera-Viedmas et al [8] only requires $n-1$ judgments for a preference matrix with n elements. The following describes the procedures for obtaining the priorities of influential factors.

1) Construct pairwise comparison matrices amongst the influential factors ($F_i, i=1,2,\dots,n$). The evaluators ($E_k, k=1,2,\dots,m$) then are asked which is the more important of each two influential factors for a set of $n-1$ preference values $\{a_{12}, a_{23}, \dots, a_{n-1n}\}$, for example:

$$A^k = \begin{matrix} & F_1 & F_2 & F_3 & \dots & F_n \\ \begin{matrix} F_1 \\ F_2 \\ F_3 \\ \vdots \\ F_n \end{matrix} & \begin{bmatrix} 1 & a_{12}^k & \times & \times & \times \\ \times & 1 & a_{23}^k & \times & \times \\ \times & \times & 1 & a_{34}^k & \times \\ \vdots & \vdots & \vdots & \ddots & a_{n-1n}^k \\ \times & \times & \times & \times & 1 \end{bmatrix} \end{matrix},$$

where a_{ij}^k denotes the preference intensity toward factors i and j assessed by k^{th} evaluator. The sign “ \times ” indicates the remaining a_{ij}^k which can be done by inverse comparison methods.

2) Transform the preference value a_{ij}^k into p_{ij}^k in an interval scale $[0,1]$, then obtain the remaining p_{ij}^k by using the reciprocal transitivity property, such as

$$A^k \xrightarrow{\frac{1}{2}(1+\log_9 a_{ij}^k)} P^k = \begin{matrix} & F_1 & F_2 & F_3 & \dots & F_n \\ \begin{matrix} F_1 \\ F_2 \\ F_3 \\ \vdots \\ F_n \end{matrix} & \begin{bmatrix} 0.5 & p_{12}^k & \times & \times & \times \\ 1-p_{12}^k & 0.5 & p_{23}^k & \times & \times \\ \times & 1-p_{23}^k & 0.5 & p_{34}^k & \times \\ \vdots & \vdots & \vdots & \ddots & p_{n-1n}^k \\ \times & \times & \times & \times & 0.5 \end{bmatrix} \end{matrix}$$

The remaining p_{ij}^k can be calculated using Eqs. (2) and (10).

3) Utilize the method of average value to integrate the judgment values of m evaluators, namely

$$p_{ij} = \frac{1}{m}(p_{ij}^1 + p_{ij}^2 + \dots + p_{ij}^m), \quad (9)$$

4) Use r_{ij} to indicate the normalized fuzzy preference values of each influential factor, such as

$$r_{ij} = \frac{p_{ij}}{\sum_{i=1}^n p_{ij}}, \quad (10)$$

5) Given the \bar{w}_i denoting the priority weight of influential factor i , the priority weight of each factor can be obtained, that is

$$\bar{w}_i = \frac{\sum_{j=1}^n r_{ij}}{\sum_{i=1}^n \sum_{j=1}^n r_{ij}}, \quad (11)$$

3.3. Determining the Priority Ratings for Possible Outcome Regarding Factors

The evaluators are asked to express their subjective judgments regarding the preference ratings of possible outcome ($A_u, u=1,2,\dots,t$) regarding each influential factor in linguistic terms, as listed in Table 2.

1) Under each influential factor, the evaluators are asked to choose the best of two possible outcome for a set of $t-1$ preference data $\{b_{12}, b_{23}, \dots, b_{t-1t}\}$, for example

$${}_i B = \begin{matrix} & A_1 & A_2 & A_3 & \dots & A_t \\ \begin{matrix} A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_t \end{matrix} & \begin{bmatrix} 1 & {}_i b_{12}^k & \times & \times & \times \\ \times & 1 & {}_i b_{23}^k & \times & \times \\ \times & \times & 1 & {}_i b_{34}^k & \times \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \times & \times & \times & \times & 1 \end{bmatrix} \end{matrix}$$

where ${}_i b_{uv}^k$ represents the performance value assigned by evaluator k to possible outcome u and possible outcome v based on influential factor i .

2) Next, the preference value ${}_i b_{uv}^k$ is transformed in the range $[\frac{1}{5}, 5]$ into ${}_i q_{uv}^k$ in an interval scale $[0,1]$, and the remaining ${}_i q_{uv}^k$ can be obtained using the reciprocal transitivity property as follows

$${}_i B \Rightarrow {}_i Q = \begin{matrix} & A_1 & A_2 & A_3 & \dots & A_t \\ \begin{matrix} A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_t \end{matrix} & \begin{bmatrix} 0.5 & {}_i q_{12}^k & \times & \times & \times \\ 1-{}_i q_{12}^k & 0.5 & {}_i q_{23}^k & \times & \times \\ \times & 1-{}_i q_{23}^k & 0.5 & {}_i q_{34}^k & \times \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \times & \times & \times & \times & 0.5 \end{bmatrix} \end{matrix}$$

3) Use the method of average value to integrate the judgment values of m evaluators; that is

$${}_i q_{uv} = \frac{1}{m} ({}_i q_{uv}^1 + {}_i q_{uv}^2 + \dots + {}_i q_{uv}^m), \quad (12)$$

4) Take ${}_i \lambda_{uv}$ to indicate the normalized rating of possible outcomes u and v with respect to influential factor i , for example

$${}_i \lambda_{uv} = \frac{{}_i q_{uv}}{\sum_{u=1}^t {}_i q_{uv}}, \quad u, v = 1, 2, \dots, t, \quad (13)$$

5) Consequently, ${}_i \bar{\phi}_u$ denoting the average rating of possible outcome u with respect to influential factor i is provided. The desired rating of each possible outcome can be obtained for each influential factor, that is,

$${}_i \bar{\phi}_u = \frac{1}{t} \sum_{v=1}^t \lambda_{uv}, \quad (14)$$

where t presents the number of possible outcome.

3.4. Obtaining the Priority Weight for Prediction

Multiplying the priority weights of influential factors by the ratings of possible outcomes, a predicted value Z_u for chance in success/failure implementation is obtained as:

$$Z_u = \sum_{i=1}^n {}_i \bar{\phi}_u \bar{\omega}_i, \quad (15)$$

4. Empirical Analysis

A semiconductor engineering company located in Taiwan wishes to increase benefit and gain competitive competency by initiating advanced manufacturing technology. Since the AMT implement consumes considerable financial and time resources, careful planning is needed before embarking AMT. Therefore, the CEO asks a group comprising three senior managers, two IT representatives, two AMT project representatives and two random sampling staff to analyze the chance of successful AMT implementation.

4.1. Weighting Calculation of the Influential Factors

Six major influential factors are considered in this problem of predicting the success of AMT implementation. The pairwise comparisons for these seven factors are obtained via a series of interviews with the assessment representatives.

1) Based on the interviews with 9 representatives regarding the importance on six influential factors, the pairwise comparison matrices for a set of $n-1$ neighboring factors are listed in Table 3.

2) The assessment of evaluator 1 is used as an example, and the linguistic terms can be transferred into corresponding numbers as listed in Table 4.

Table 3. The linguistic terms toward seven factors assessed by 11 evaluators.

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	
F_1	VS	ST	AV	WK	LSLV	AV	SW	AB	ST	F_2
F_2	LSLV	ST	LST	LVS	LST	VS	WE	LST	LST	F_3
F_3	LVLA	LWK	LAB	LVLA	WK	LST	LST	LVLA	LAB	F_4
F_4	VT	SW	VS	VS	ST	LVS	LVS	LSLV	LWK	F_5
F_5	LAB	LVLA	LSLV	LAB	LVLA	LVLA	LAB	LVS	LVLA	F_6

Table 4. Transformed fuzzy preference values of evaluator 1.

E_1	F_1	F_2	F_3	F_4	F_5	F_6
F_1	0.500	0.943	0.535	0.062	0.470	-0.030
F_2	0.057	0.500	0.092	-0.381	0.027	-0.473
F_3	0.465	0.908	0.500	0.027	0.435	-0.065
F_4	0.938	1.381	0.973	0.500	0.908	0.408
F_5	0.530	0.973	0.565	0.092	0.500	0.000
F_6	1.030	1.473	1.065	0.592	1.000	0.500

3). Eq.(3) was used to transform the elements (listed in Table 4) into an interval [0,1], yielding the following values:

$$p_{12} = (1 + \log_9 7) / 2 = 0.943;$$

$$p_{23} = (1 + \log_9 \frac{1}{6}) / 2 = 0.092$$

$$p_{34} = (1 + \log_9 \frac{1}{8}) / 2 = 0.027;$$

$$p_{45} = (1 + \log_9 6) / 2 = 0.90$$

$$p_{56} = (1 + \log_9 \frac{1}{9}) / 2 = 0;$$

$$p_{67} = (1 + \log_9 5) / 2 = 0.866$$

4) The remaining values then can be calculated by Eqs. (4) and (5). For p_{21} , p_{31} , and p_{52} as examples,

$$p_{21} = 1 - p_{12} = 1 - 0.943 = 0.057$$

$$p_{31} = \frac{3-1+1}{2} - p_{12} - p_{23} = 0.465$$

The fuzzy preference relation matrix for seven influential factors assessed by evaluator 1 can be established in Table 4. Table 4 lists ten elements not in the interval [0,1], and thus a linear transformation stated in Eq. (8) is employed to ensure the reciprocity and additive transitivity for the preference relation matrix. Table 5 lists the transformation matrix.

4) Likewise, the same computational procedures (1)-(3) stated above can calculate the fuzzy preference relation matrices of the other ten evaluators; therefore, using Eq (9), the aggregated pairwise comparison matrix of eleven evaluators can be obtained as listed in Table 6.

5) Equation (10) is used to normalize the aggregated pairwise comparison matrix. The priority weight of each influential factor can then be obtained by Eq (11). The priority weight and rank of each influential factor assessed by eleven evaluators are listed in Table 7.

Table 5. Preference values transformed by linear solution.

E_1	F_1	F_2	F_3	F_4	F_5	F_6
F_1	0.500	0.728	0.518	0.275	0.484	0.228
F_2	0.272	0.500	0.291	0.047	0.257	0.000
F_3	0.482	0.709	0.500	0.257	0.466	0.209
F_4	0.725	0.953	0.743	0.500	0.709	0.453
F_5	0.516	0.743	0.534	0.291	0.500	0.243
F_6	0.772	1.000	0.791	0.547	0.757	0.500

Table 6. Aggregated pairwise comparison matrices of 9 evaluators.

	F_1	F_2	F_3	F_4	F_5	F_6
F_1	0.500	0.629	0.557	0.407	0.473	0.250
F_2	0.371	0.500	0.428	0.278	0.343	0.120
F_3	0.443	0.572	0.500	0.350	0.415	0.192
F_4	0.593	0.722	0.650	0.500	0.565	0.342
F_5	0.527	0.657	0.585	0.435	0.500	0.277
F_6	0.750	0.880	0.808	0.658	0.723	0.500
Total	3.184	3.959	3.528	2.628	3.019	1.681

Table 7. Normalized matrix of priority weight and rank of influential factors.

	F_1	F_2	F_3	F_4	F_5	F_6	Total	Weight	Rank
F_1	0.157	0.159	0.141	0.155	0.157	0.148	0.917	0.156	4
F_2	0.116	0.126	0.108	0.106	0.114	0.072	0.642	0.109	6
F_3	0.139	0.144	0.126	0.133	0.137	0.114	0.795	0.135	5
F_4	0.186	0.182	0.164	0.190	0.187	0.203	1.113	0.189	2
F_5	0.166	0.166	0.148	0.165	0.166	0.165	0.975	0.166	3
F_6	0.236	0.222	0.204	0.250	0.239	0.297	1.449	0.246	1

4.2. Calculation of the Weights for Possible Outcomes with Respect to Influential Factors

If an influential factor has a strong presence in the company, then AMT implementation is more likely to be successful. To determine the priority weight matrix for possible outcomes with respect to each influential factor, the linguistic variables for evaluators are listed in Table 2. The priority weights of two possible outcomes are calculated as follows.

1) Examining the actual circumstances of this company, the 11 evaluators are interviewed to assess which is more likely to occur according to each influential factor. Table 8 lists the opinions of these 9 evaluators regarding the preference intensity for the chance of success and failure with respect to each influential factor.

Table 8. Linguistic variables given to the priority weight of two possible outcomes.

		E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9
		F	F	F	F	F	F	F	F	F
F_1	S	H	LHF	VH	VH	F	H	VHG	H	VHG
F_2	S	LVH	VHG	VHG	LH	HF	H	VHG	H	H
F_3	S	VHG	VH	HF	HF	LHF	H	LHF	HF	LHF
F_4	S	VH	H	VHG	H	H	VHG	H	H	H
F_5	S	HF	H	H	LHF	H	F	H	HF	H
F_6	S	VH	H	H	F	H	H	VH	VH	VHG

Note: **S**, **F** denoting the abbreviation of success and failure respectively.

2) Translate the linguistic variables into corresponding numbers defined in Tables 2. Then use this function, $p_{ij} = \frac{1}{2} \cdot (1 + \log_5 a_{ij})$, to transform the values in the scale $[\frac{1}{5}, 5]$ into the interval $[0,1]$. The transformed preference data are shown in Table 9.

3) With the reciprocal additive transitivity property, the inverse comparison for failure and success can be calculated.

4) Using Eq. (12), the synthetic rating of possible outcomes can be obtained as listed in Table 10. Eqs. (13)-(14) then can be used to normalize and synthesize the fuzzy preference rating of two possible outcomes based on seven influential factors. The

normalized values and priority weights are listed in Table 10.

Table 9. Transformed preference weight of possible outcome in relation to factors.

		E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9
		F	F	F	F	F	F	F	F	F
F_1	S	0.159	0.715	0.000	0.000	0.500	0.159	0.069	0.159	0.069
F_2	S	1.000	0.069	0.069	0.841	0.285	0.285	0.159	0.069	0.159
F_3	S	0.069	0.000	0.285	0.285	0.715	0.159	0.715	0.285	0.715
F_4	S	0.000	0.159	0.069	0.159	0.159	0.069	0.159	0.159	0.159
F_5	S	0.285	0.159	0.159	0.715	0.159	0.500	0.159	0.285	0.159
F_6	S	0.000	0.159	0.159	0.500	0.159	0.159	0.000	0.000	0.069

Table 10. Normalized priority weights of possible outcome based on seven factors.

		Success	Failure	Total	Priority Weight
F_1	Success	0.750	0.566	1.316	0.658
	Failure	0.250	0.434	0.684	0.342
F_2	Success	0.652	0.524	1.176	0.588
	Failure	0.348	0.476	0.824	0.412
F_3	Success	0.630	0.512	1.142	0.571
	Failure	0.370	0.488	0.858	0.429
F_4	Success	0.834	0.590	1.424	0.712
	Failure	0.166	0.410	0.576	0.288
F_5	Success	0.681	0.539	1.220	0.610
	Failure	0.319	0.461	0.780	0.390
F_6	Success	0.820	0.586	1.407	0.703
	Failure	0.180	0.414	0.593	0.297

4.3. Determining the Priority Weights for Prediction

Using Eq. (15), the prediction weights of the chances for successful and failure AMT implementation is determined as shown in Table 11. For example, the prediction weight for successful AMT implementation is calculated as

$$Z_1 = (0.658 * 0.156 + 0.588 * 0.109 + 0.571 * 0.135 + 0.712 * 0.189 + 0.610 * 0.166 + 0.703 * 0.246) = 0.652$$

Table 11. Prediction probabilities of “success” and “failure”.

	F_1	F_2	F_3	F_4	F_5	F_6	Prediction probability
Factor weight	0.156	0.109	0.135	0.189	0.166	0.246	
Success	0.658	0.588	0.571	0.712	0.610	0.703	0.652
Failure	0.342	0.412	0.429	0.288	0.390	0.297	0.348

5. Conclusions

For enterprises and organizations, growing revenues, increasing profits, improving customer service, shortening product-manufacturing cycle and enhancing competitive competency are cited as objectives for motivating advanced manufacturing technology initiatives. To cope with qualitative influential factors in subjective environments, linguistic variables transformed into an interval [0,1] are employed to derive the priority weights of key influential factors and the predicted weight of successful sensors AMT implementations. Furthermore, an empirical sensors AMT implementation case involving a semiconductor company in Taiwan is used to demonstrate the implementation of this approach. Besides fulfilling an examining role in helping organizations to gain awareness of their weaknesses in prediction processes, this study also provides decision makers with useful information to make decision regarding whether to initiate sensors AMT, inhibit adoption or undertake some remedial improvement actions to increase the possibility of successful sensors AMT implementation. The empirical results not only demonstrate that organizational culture, application of technology and leadership of superintendent are the three most important influential factors in the sensors AMT initiative process, but also reveal the applicability and feasibility of reciprocal additive consistent fuzzy preference relation for solving complicated hierarchical multiple attribute prediction problems.

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