A Multiple Criteria Decision Making Based Performance Measurement and Improvement Model for Lean Manufacturing Activities


Abstract—A steady and sustained increase in Lean Manufacturing (LM) applications have been observed in organisations of all sizes in virtually all sectors of manufacturing industries. Although monitoring and evaluating effectiveness of LM is an important aspect, it is generally agreed that there is a lack of appropriate Performance Measurement and Improvement Systems (PMIS) for LM activities. This paper describes the development of a PMIS framework that is applicable to organisations of various sizes (large, medium and small companies) within a range of industries. The proposed PMIS framework is based on a Multiple Criteria Decision Making (MCDM) approach based on Fuzzy Analytical Hierarchy Process (FAHP). In the proposed model Key Performance Indicators (KPIs) are organized within 8 parameters containing 66 second level lean practices indicators. The decision making process involves the choice of optimal preference for LM improvement, which often involves complex, conflicting requirements among the KPIs and lean practices indicators. A new method to fuzzy vagueness and uncertainty in human judgment into crisp scores from pair wise comparison is introduced. A numerical example is used to illustrate the use of the model. A case study involving a manufacturing organisation is underway and results will be published in due course.

Keywords—Fuzzy AHP, Lean Manufacturing, Performance Measurement.

I. INTRODUCTION

There is a number of Performance Measurement Systems (PMS) to suit a variety of contexts. Choosing an appropriate PMS is not an insignificant task. Preferred PMS would have a direct impact on the outcomes of the particular lean manufacturing implementation. An appropriate PMS will allow the management to achieve an optimum performance right from the planning stages to the manufacturing stages.

Traditionally, the development of a PMS is based on financial data from conventional accounting systems such as earning per share, return of investment, purchase price variance and machine utilization. Neely et al [1] argued that such measures only consider the efficiency and productivity aspects. Hence, such a PMS merely measures the final result of activities but does not measure important aspects such as efficiency (or waste) and effectiveness of these activities. As a result the conventional PMS tends to measure only the outcomes of past decisions but fails to give an indication for any future performance improvements.

Given the complexity, diversity and dynamic developments of business environment many academics and industry practitioners believe that conventional financial performance measures are inadequate for the present manufacturing environment [2]. Further, Dixon et al [2] argued that a performance measurement system must be regularly updated in order to support the continuous evolutionary changes in manufacturing practices. Crawford and Cox [3] recognise the need for continuous changes for an effective performance measurement system to reflect the continuous evolutionary changes in the business and manufacturing environments.

An appropriate PMS on a lean manufacturing company needs not only to measure performance but also to improve the system by identifying the optimum applications of lean tools and techniques. Meanwhile, Pun and White [4] argued that performance measurement should facilitate decision making to align actions with strategic objectives and provide feedback on operational performance and internal capabilities to the strategic level. In this paper the main objective is to describe the development of a conceptual framework of Performance Measurement and Improvement Systems (PMIS), which is based on Multiple Criteria Decision Making (MCDM), using Fuzzy Analytical Hierarchy Process (FAHP) for lean manufacturing activities.

II. MULTI CRITERIA DECISION MAKING (MCDM)

Decision making methods can be separated into two groups: (1) crisp based decision methods and (2) fuzzy based decision methods. In crisp based decision making, an evaluator uses a crisp value to rank an alternative while in fuzzy based, the evaluator uses a fuzzy value to rank the alternative. The most popular methods of crisp based decision making are: Weight
Sum Model (WSM), Weight Product Model (WPM), Analytic Hierarchy Process (AHP), Revised Analytic Hierarchy Process (RAHP) and ANP (Analytical Network Process). Fuzzy based decision making are based on AHP methods known as fuzzy AHP. The first generation of fuzzy AHP is introduced by Van Laarhoven and Pedrycz [5] which was followed by researcher such as Jung and Lee [6] and Levary and Ke [7]. Among the crisp based value method, Taloy [8] found that the AHP is the best methods particularly for problems with multiple criteria. However, AHP is inadequate to deal with problems involving imprecise judgments [9]. Kulak and Kahraman [10] found that humans tend to be relatively ineffective in making quantitative predictions, whereas they are comparatively efficient in qualitative forecasting. Essentially, the uncertainty in preferential judgments gives rise to uncertainty in the ranking of alternatives as well as difficulty in determining consistency of preferences [9]. Fuzziness and vagueness existing in many decision-making problems may contribute to the imprecise judgments of decision makers in conventional AHP approaches (Bouyssou et al [11]). There are instances in which imprecision and vagueness lead to instability and inconsistency in AHP computations [11]. To avoid this stability Fuzzy AHP uses an averaging procedure to calculate weighting factor that would avoid the occurrence of instability.

Most publication on fuzzy AHP is on methods for finding weighting factor, known as fuzzy priority. Chang [12], for example, published a method for fuzzy priorities called synthetic extent analysis. Later, Mikhailov [13] found that synthetic extent analysis can work well if comparison matrix is consistent. Yu [14] used a linearization and fuzzy rating techniques for finding weight of criteria. However less attention has been given to consistence problem of comparison matrix [15-16]. Harker [15] improves an inconsistent matrix by reconsider pair-wise comparisons. Ishizaka and Lusti [16] rearrange comparison matrix in order to have a consistent matrix. Both methods can affect decision result due to changes made to the comparison matrix. This paper proposed a method to improve consistence of the comparison matrix and apply the method to Lean performance measurement and improvement.

A. Fuzzy Analytic Hierarchy Process

Original Analytics Hierarchy Procedure (AHP) uses crisp numbers in comparing one alternative over another. Comparison judgment depends on human perception which always contain vagueness and imprecision. Crisp number often fails to capture this vagueness [17]. In order to capture the imprecision of human judgment a fuzzy concept is introduced to the AHP method.

B. Fuzzy Theory

The fuzzy theory was introduced by Zadeh [18] to deal with uncertainty caused by vagueness or imprecision. A fuzzy set is a collection of an object with graded membership. Grading of the object is represented by a membership function attached to the object. The membership function of a fuzzy set A is expressed as with a value between 0 and 1. If a factor x is strongly associated with set A, is 1 and if it definitely does not belong to set A, is 0, i.e. the higher the membership function value the higher the confidence that the factor is associated with set A, (Timothy [19]).

Definition 1 (fuzzy set)

Assumed X is a universe of discourse, \( \tilde{A} \) is a fuzzy number and subset of X. For \( x \in X \) there is a number \( \mu_{\tilde{A}}(x) \in (0,1) \) assigned to the representation of x to \( \tilde{A} \) and \( \mu_{\tilde{A}}(x) \in (0,1) \) is called the membership function of \( \tilde{A} \).

Definition 2 (fuzzy number)

Assumed X is a universe of discourse; a fuzzy number \( \tilde{A} \) is a normal and convex subset of X. So that \( \forall x_1 \in X \), \( \forall x_2 \in X \), \( \forall \beta \in [0,1] \)

The following condition is satisfied:

\[
\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda)x_2) = \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2))
\]

Definition 3 (triangular fuzzy number)

Triangular fuzzy number \( \tilde{A} \) defined by a triplet \( \tilde{A} = (a_l, a_m, a_r) \). The membership function \( \mu_{\tilde{A}}(x) \) with its highest value is assign for \( a_m \) due to \( a_m \) is considered strongly belong to \( \tilde{A} \) and \( \mu_{\tilde{A}}(x) \) decrease toward \( a_l \) and \( a_r \). The membership function is defined as following:

\[
\mu_{\tilde{A}}(x) = \begin{cases} 
\frac{x-a_l}{a_m-a_l} & a_l \leq x \leq a_m \\
\frac{a_m-x}{a_m-a_r} & a_m \leq x \leq a_r \\
0 & a_r \leq x \leq a_l 
\end{cases}
\]  

(1)

Gonzalez et al [21] defined the Geometrix mean of fuzzy \( \tilde{A} \) and \( \tilde{B} \) is \( \tilde{C} = ((a_l \times b_r)^{1/2}, (a_m \times b_m)^{1/2}, (a_r \times b_l)^{1/2}) \).

Fuzzy number \( \tilde{A} \) can be converting to crisp number A using centroid formula of Wang et al [20]:

\[
A = \frac{a_l + a_m + a_r}{3}
\]  

(3)

Preposition 1 (information of fuzzy number) [21] can be represented through an information function 1:

\[
I_r : R \rightarrow [0,1], \forall A \in R, \quad I_r(\tilde{A}) = \frac{h(\tilde{A})}{f(\tilde{A})} + 1
\]  

(4)

Where \( h(\tilde{A}) \) is level of certainty of fuzzy number \( \tilde{A} \), i.e. maximum height of membership function, and \( f(\tilde{A}) \)
represent imprecision associated with fuzzy number \( \tilde{A} \). 
\( f(\tilde{A}) \) is an area under membership function.

**Preposition 2** (similarity of fuzzy number) [22], the similarity of two fuzzy number \( \tilde{A} \) and \( \tilde{B} \) are measured by using similarity function as following [21]:

\[
S(\tilde{A}, \tilde{B}) = \frac{1}{1 + d(\tilde{A}, \tilde{B})}
\]  

(5)

Where:

\[
d(\tilde{A}, \tilde{B}) = |P(\tilde{A}) - P(\tilde{B})|,
\]

\[
P(\tilde{A}) = \frac{a_1 + 2a_{m1} + 2a_{m2} + a_r}{6},
\]

\[
P(\tilde{B}) = \frac{b_1 + 2b_{m1} + 2b_{m2} + b_r}{6}.
\]

Gonzales et al. [21] suggest that two fuzzy number are similar if both have same information function \( I_f \), while Hsieh & Chen [22] claimed that the similarity depend on similarity function \( S \) where two fuzzy number are similar if \( S = 1 \).

**Preposition 3** (new similarity of fuzzy number). A fuzzy number \( \tilde{A}(a_1, a_m, a_r) \) which have maximum membership function of \( \alpha \) is similar to a fuzzy number \( \tilde{B}(b_1, b_m, b_r) \) which have maximum membership function of 1 if the following condition is satisfied:

\[
\frac{h(\tilde{A})}{f(\tilde{A}) + 1} = \frac{h(\tilde{B})}{f(\tilde{B}) + 1},
\]

\[
d(\tilde{A}, \tilde{B}) = 0
\]  

(6)

Proof: based on Preposition 1 and Preposition 2. According to preposition 3, if two fuzzy numbers \( \tilde{A}(a_1, a_m, a_r) \) and \( \tilde{B}(b_1, b_m, b_r) \) which have maximum membership function of \( \alpha \) and 1 respectively and \( a_m = b_m \), by using on Equation (5) and (6), it can be shown that:

\[
b_1 = a_1 - \frac{1}{\alpha} + 1
\]  

(7)

\[
b_r = a_r + \frac{1}{\alpha} - 1
\]  

(8)

Fuzzy number \( \tilde{A}(a_1, a_m, a_r) \) and \( \tilde{B}(b_1, b_m, b_r) \) are illustrated in Figure 1.

III. FRAMEWORK OF PERFORMANCE MEASUREMENT

The proposed framework for performance measurement system for a manufacturing company consists of the following steps:

1. Identify key performance indicators (KPIs) of lean and lean practices indicators, which will have significant influence on company performance.
2. Find degree of importance, also known as weight, of each lean KPI and lean practices indicators using FAHP.
3. Collect the information of achievement in the KPIs and lean practices in point (1) and calculate their scores.
4. Calculate lean performance based on weight in step (2) and scoring of lean practices in step (3).

A. Identify Lean performance indicators and Lean practices indicators

There are differences in opinions regarding the relevant indicators contributing towards the measure of lean activities. Indicators used in this paper are selected based on the definition of leaness from an extensive literature review of papers and work, such as Anand and Kodali [23], Singh et al [24], Saurin and Ferriera [25], Doolen and Hacker [26], Karlsson and Ahlstrom [27], related to components of lean practices. The result of this survey reveals a set of “common denominators”: a set of eight key performance indicators which contain sixty six (66) lean practices indicators. The eight of key performance indicators of lean are Customer Issue, Supplier Issue, Manufacturing Management, Internal Business Management, Manufacturing Efficiency, Research and Development, Learning Prospective and Investment Priority as shown in Figure 2.

B. The Proposed Fuzzy AHP

Application of Fuzzy number for capture uncertainty of human judgment in AHP was introduced by Laarhoven and pedrycz [5]. In the original AHP of Saaty [28] a decision maker expresses judgment about the importance of one alternative over another by a crisp number. The proposed Fuzzy AHP deals with vagueness of the judgment by translating this to a fuzzy number with triangular membership function with central value of the fuzzy number corresponding to the crisp number given by the decision maker. The judgment from several decision makers is then aggregated and arithmetic mean operation of fuzzy number is then used within a procedure to calculate the weight vector. An AHP is established into hierarchical structure of interrelated decision, which consists of the goal, lean indicators and lean sub-indicators/alternatives (Figure 2). In the first level is goal i.e. companies overall performance measurement and improvement. The goal is break into the eight of KPIs of lean activities, and each KPI has alternatives for performance improvement of lean activities at the industrial manufacturing companies.

The complete steps of Fuzzy AHP used in this proposed method are as follows: establish decision group; member of decision groups make judgment on importance of lean
practice; aggregate judgments of decision maker; check
consistency; and calculate the weight.

**Establish decision group.** This is the group of people with
relevant expertise who will express judgment about the
relative importance of one alternative over another. The
decision group should be selected to express representative
view corresponding to the real condition. There are at least
two considerations that should be used to achieve this
condition. Firstly, some members of should be industrial
practitioner from relevant fields both in the technical and
managerial positions. Secondly, the remained members should
be academics with appropriate research knowledge. In this
way a balanced view from practitioners and academic
perspectives can be achieved.

Member of decision groups make judgment on importance
of lean practice using pair wise comparison. The members
of the decision group make judgment of relative preference
and importance of one lean practice parameter over another
with pair wise comparison on a scale of 1-9. The pair wise
comparison produces a crisp score of relative preference
and importance. In addition each member will also indicate
people degree of confidence in judgment for the given
parameter (with \( a = 0 \) as 0% confidence and \( a = 1 \) as 100%
confidence). In this way the crisp score awarded by a member
of the decision group can be transformed to a fuzzy number to
account for vagueness using the triangle membership function
as described (see Table 1). If a decision maker indicates a
confidence level of \( \alpha \%), the height of the membership
function is \( \alpha \). The fuzzy number with the indicated
confidence of \( \alpha \) is then normalized using equations (6) and
(7).

<table>
<thead>
<tr>
<th>Scale of relative importance (Crisp number)</th>
<th>Triangular fuzzy number</th>
<th>Linguistic variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(1,1,1)</td>
<td>equally important</td>
</tr>
<tr>
<td>3</td>
<td>(4-a,4,4+a)</td>
<td>moderate important</td>
</tr>
<tr>
<td>5</td>
<td>(5-a,5,5+a)</td>
<td>strong important</td>
</tr>
<tr>
<td>7</td>
<td>(7-a,7,7+a)</td>
<td>very strong important</td>
</tr>
<tr>
<td>9</td>
<td>(9-a,9,9)</td>
<td>absolutely important</td>
</tr>
<tr>
<td>( x=2,4,6,8 )</td>
<td>( x-a,5,5+a )</td>
<td>a value between 2 level</td>
</tr>
</tbody>
</table>

The resultant pair wise comparison of \( n \) lean practices
parameters is then given by:

\[
\begin{bmatrix}
\tilde{c}_{11}, & \tilde{c}_{12}, & \tilde{c}_{13}, & \tilde{c}_{1n} \\
\tilde{c}_{21}, & \tilde{c}_{22}, & \tilde{c}_{23}, & \tilde{c}_{2n} \\
\tilde{c}_{n1}, & \tilde{c}_{n2}, & \tilde{c}_{n3}, & \tilde{c}_{nn}
\end{bmatrix}
\]

where, subscript \( i \) represents the \( j^{th} \) decision maker and
subscript \( jk \) in \( c_{jk} \) represent preference of lean practice \( j^{th} \)
again lean practice \( k^{th} \), the lean practice itself is those in
Figure 2. In this pair wise comparison, \( c_{jk} = \frac{1}{c_{kj}} \).

**Aggregate judgments of decision makers.** Fuzzy pair wise
comparison from several decision makers are now ready to be
combined to form an overall group decision. There are two
common methods to form the aggregation: i.e. the simple
arithmetic average method and the min-max method proposed
by Chang et al. [30] are not appropriate. For this work a
geometric mean method is regarded as a more appropriate
method. In the simple arithmetic average, aggregation of two
fuzzy numbers from two decisions maker \( i^{th} \) and \( s^{th} \), is
calculated as:

\[
\bar{c}_{jk} = \frac{\tilde{c}_{kji} + \tilde{c}_{kjs}}{2} = \left( \frac{a_{i} + a_{j}}{2}, \frac{a_{m} + a_{j}}{2}, \frac{a_{n} + a_{j}}{2} \right) (9)
\]

Where:

\[
\tilde{c}_{kji} = (a_{i}, a_{m}, a_{n}) \text{ is the relative score of importance of Lean Practice (LP) } j^{th} \text{ against lean practice } k^{th} \text{ by decision maker } i^{th} \ .
\tilde{c}_{kjs} = (a_{i}, a_{m}, a_{n}) \text{ is score of importance of LP } j^{th} \text{ against lean practice } k^{th} \text{ by decision maker } s^{th} \ .
\]

Because \( c_{kji} = \frac{1}{c_{kjs}} \) and \( c_{kij} = \frac{1}{c_{kji}} \), \( c_{kj} \) is calculated as:

\[
\bar{c}_{kj} = \frac{\tilde{c}_{kji} + \tilde{c}_{kjs}}{2} = (0.5(\frac{1}{a_{i}} + \frac{1}{a_{s}}), 0.5(\frac{1}{a_{m}} + \frac{1}{a_{s}}), 0.5(\frac{1}{a_{n}} + \frac{1}{a_{s}})) (10)
\]

From Equation (9) and Equation (10), it can be shown:

\[
c_{jk} \neq c_{kj} \ , \text{ this result violate one of the AHP’s rule of consistancy. Hence the simple arithmetic average method is not appropriate for the work. The min max operator of Chang [30] is expressed as:}
\]

\[
\bar{c}_{jk} = (\text{min}(a_{i}), (\Pi_{r=1}^{p} a_{mr})^{\frac{1}{p}}, \text{max}(a_{r})) \]

Where subscript \( t \) represents \( t^{th} \) decision maker and \( p \) is
number of decisions maker. The min max operation is not
appropriate if at least one decision maker give very low or
very high preference score which will give rise to a huge span
of aggregated fuzzy number. In this work geometric mean is
defined as:

\[
\bar{c}_{jk} = (\prod_{r=1}^{p} a_{ir})^{\frac{1}{p}} \cdot (\prod_{r=1}^{p} a_{mr})^{\frac{1}{p}} \cdot (\prod_{r=1}^{p} a_{nr})^{\frac{1}{p}} \]

(12)
Fig. 2 A hierarchy framework for PMIS of lean manufacturing activities
Upon aggregation of every pair wise comparison, a final comparison matrix resulted is:

\[
\begin{bmatrix}
  c_{11} & c_{12} & c_{13} & \cdots & c_{1n} \\
  c_{21} & c_{22} & c_{23} & \cdots & c_{2n} \\
  \vdots & \vdots & \vdots & \ddots & \vdots \\
  c_{n1} & c_{n2} & c_{n3} & \cdots & c_{nn}
\end{bmatrix}
\]

Where \( c_{ij} \) is preference of lean practice \( i^{th} \) compared to lean practices \( j^{th} \). In this case \( c_{ji} = 1/c_{ij} \).

**Check consistency.** In order to check the consistency of comparison matrix, the fuzzy members of the matrix \( \bar{c} \) need to be converted to their related crisp value by using defuzzy procedure as explain in previous section, Eq. (3), to have crisp comparison matrix as follow:

\[
\begin{bmatrix}
  c_{11} & c_{12} & c_{13} & \cdots & c_{1n} \\
  c_{21} & c_{22} & c_{23} & \cdots & c_{2n} \\
  \vdots & \vdots & \vdots & \ddots & \vdots \\
  c_{n1} & c_{n2} & c_{n3} & \cdots & c_{nn}
\end{bmatrix}
\]

Where: \( c_{ij} = \frac{a_i + a_m + a_r}{3} \)

Consistence of comparison matrix is measured by consistence ratio:

\[
CR = \frac{CI}{RI}, \quad CI = \frac{\lambda_{\text{max}} - n}{n - 1}
\]

Where \( \lambda_{\text{max}} \) is largest Eigen value of comparison matrix \( c \), \( RI \) is random index, which shown in Table 2 and \( n \) is matrix size. Saaty [28] suggested that if \( CI < 0.1 \) matrix \( c \) is consistent.

**Calculate the weight.** Based on idea of Buckley [31], weight of lean practices \( t^{th} \) is calculated as geometric mean of elements in raw \( t^{th} \) of fuzzy comparison matrix which normalized by sum of geometric mean of all raw. According to equation (2), the geometric mean of raw \( t \) is:

\[
\bar{r}_t = \left( \prod_{s=1}^{n} c_{ts} \right)^{1/n}
\]  

Finally the weight of lean practice \( t^{th} \) is:

\[
\tilde{w}_t = \bar{r}_t \otimes \left( \sum_{t=1}^{n} \bar{r}_t \right)^{-1}
\]

Crisp value of weight is found by defuzzified the weight \( \tilde{w}_t \) using Equation (3).

**C. An Illustrative Example**

In this example (A) represents the amount of hour of training given to new employed personal (B) represents the use of visual management aids and (C) represents training for employees to perform three or more jobs i.e. multi skills. Also it is assumed that the combined judgment from the decision group is shown in Table 3.

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>JUDGMENT SCORE FORM EVALUATORS</th>
</tr>
</thead>
<tbody>
<tr>
<td>A B C</td>
<td>A 1 5 7</td>
</tr>
<tr>
<td>A B C</td>
<td>B 1/5 1 1/3</td>
</tr>
<tr>
<td>A B C</td>
<td>C 1/7 3 1</td>
</tr>
</tbody>
</table>

The crisp value in Table 3 is converted to triangular fuzzy numbers, which based on the Table 2. For simplicity 100% confidence level is assumed i.e. scale of relative importance, \( \sigma = 1 \) [29]. Aggregate judgments of decision makers used equation 9.

<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>FUZZY NUMBER OF DATA OF JUDGMENTS EVALUATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>A B C</td>
<td>A (1, 1, 1) (4, 5, 6) (6, 7, 8)</td>
</tr>
<tr>
<td>A B C</td>
<td>B (1/6, 1/5, 1/4) (1, 1, 1) (1/4, 1/3, 1/2)</td>
</tr>
<tr>
<td>A B C</td>
<td>C (1/8, 1/7, 1/6) (2, 3, 4) (1, 1, 1)</td>
</tr>
</tbody>
</table>

Check consistency of the matrix

\[
N = \begin{bmatrix}
0.1 & 0.2 & 0.3 \\
0.1 & 3 & 1
\end{bmatrix}
\]

\[
\text{Eigenvector} = \begin{bmatrix} 0.75 \\ 0.09 \end{bmatrix} \begin{bmatrix} 0.15 \end{bmatrix} = \begin{bmatrix} 0.75 \\ 0.09 \end{bmatrix}
\]

\[
\lambda_{\text{max}} = \begin{bmatrix} 1.3 & 9 & 8.3 \end{bmatrix} \times \begin{bmatrix} 0.75 \\ 0.09 \end{bmatrix} = 3.077
\]

\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1} = \frac{3.077 - 3}{3 - 1} = 0.0385
\]

\[
CR = \frac{CI}{RI} = \frac{0.0385}{0.58} = 0.06
\]

CR<0.1 the consistency is acceptable.

Calculate the weight based on equation (13) and (14).
Defuzzified the weight using equation (3); $\tilde{w} = (\tilde{w}_1, \tilde{w}_2, \tilde{w}_3)$ then is resulted: $w_1 = 0.738$, $w_2 = 0.089$ and $w_3 = 0.165$. Scores of each alternative/indicators (A, B and C) are depicted as following:

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A) amount of hour of training given to new employed personal</td>
<td>0.738</td>
</tr>
<tr>
<td>(B) use of visual management or aids</td>
<td>0.089</td>
</tr>
<tr>
<td>(C) training for employee to do three or more job/multi skill</td>
<td>0.165</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

A Fuzzy Analytical Hierarchy Process (FAHP) based Multiple Criteria Decision Making (MCDM) approach based framework for Performance Measurement and Improvement Systems (PMIS) for Lean Manufacturing (LM) activities is proposed in this paper. The proposed method can help to asses, evaluate, control and improve the impacts of decision on companies’ performance and confirms the existence of indicators interactions. To establish the framework model for PMIS, a hierarchy structure is constructed into three levels of LM activities. The first level is the goal that was expressed through by 8 KPIs in the second level and each KPI has sub-KPIs/alternatives at the third level. The proposed method uses the richness of human based judgment to determine the relative ranking of importance of KPIs in relation to the preference structure of the decision group members. A simple example is included to illustrate the proposed framework. The work has now progressed towards data collection and analysis stage with real world data from industry. Results from the data will be published in due course.

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REFERENCES


