CHAPTER VIII

METHODOLOGY DEVELOPMENT FOR SELECTION
OF BEST DECISION ALTERNATIVE

This chapter presents the methodology for the selection of best decision alternative in different stages of production system life cycle using systematic approaches i.e. integrated GTA-ISM-MOORA/PSI approaches. The methodology first utilizes the integrated GTA-ISM approach for developing a quality enabled system for the generation of decision alternatives and then utilizes MOORA/PSI method for the selection of best decision alternative.

8.1 METHODOLOGY FOR DEVELOPMENT OF DECISION ALTERNATIVES

In this section, methodology based on the integrated GTA-ISM approach has been developed for the generation of decision alternatives. The steps involved in the integrated GTA-ISM methodology are given underneath:

**Step 1:** First, select the stage in which the decision has to be efficiently made.

**Step 2:** Identify the quality enabled factors (QEFs) related to the stage under consideration. It can be attained by a survey or any group problem-solving method such as brain storming method, Delphi method. Moreover, the QEFs can be identified by the opinions of experts (academic and industrial).

**Step 3:** Group the recognized QEFs into various categories.

**Step 4:** Develop digraph (at the system level) between the major QEF categories on the basis of their interdependencies. For developing the digraph, interpretive structural modelling (ISM) approach may be utilized. ISM methodology consists of following steps:

- *Establishment of contextual relationship:* In this step, an appropriate association is recognized among the QEFs with respect to whom the pairs of QEFs would be observed. A contextual relationship of ‘leads to’ is taken for determining the relationship between the QEFs.
Development of structural self-interaction matrix (SSIM): In this step, SSIM is developed for QEFs under consideration. It is prepared on the basis of pairwise comparison of QEFs. Following symbols were used for designating the direction of relationship concerning any two QEFs (i and j):

- FR: QEF i leads to QEF j;
- BR: QEF j leads to QEF i;
- CR: QEFs i and j influences each other i.e. relation in both directions; and
- NO: QEFs i and j are unrelated i.e. no relation exists between the QEFs.

Development of reachability matrix (RM): In this step, SSIM is transformed into a binary matrix, known as initial reachability matrix (IRM). It is obtained by replacing FR, BR, CR and NO entries of SSIM by 1 and 0 digits. The guidelines for substitution of 0 and 1 digits are given below:

- If (i, j) cell value in SSIM is FR, then (i, j) cell value in IRM becomes 1 and (j, i) cell value becomes 0.
- If (i, j) cell value in SSIM is BR, then (i, j) cell value in IRM becomes 0 and (j, i) cell value becomes 1.
- If (i, j) cell value in SSIM is CR, then (i, j) and (j, i) cell value in IRM becomes 1.
- If (i, j) cell value in SSIM is NO, then (i, j) and (j, i) cell value in IRM becomes 0.

On using the above defined rules, IRM is developed. Final reachability matrix (FRM) is found by integrating the transitivity effect of ISM approach in the IRM. Transitivity (Figure 5.1) implies that if a QEF-M influences another QEF-N, QEF-N influences QEF-P, then QEF-M will also influences QEF-P.

Partition of final reachability matrix (FRM): Partition of FRM into different levels is carried out by computing the reachability set and antecedent set of each QEF from FRM. The reachability set comprises of QEF itself and other QEFs which it may influence while antecedent set comprises of QEF itself and other QEFs which may influence it. Consequently, intersection of these two
sets is computed for entire QEFs. The QEF for which reachability and intersection sets are similar, that QEF will occupy the uppermost level in the ISM model. This top level QEF will not influence or achieve other QEF about its individual level in the ISM model. After the top level QEF is recognized, it is parted out from the other QEFs. Then, the same procedure is repeated to discover the QEF in subsequent level and this process is sustained till the level of each QEF is identified. These levels aid in construction of diagraph and ISM hierarchy.

- **Development of conical matrix (CM):** Conical matrix (lower triangular matrix) is developed by converting FRM through the positioning of QEFs conferring to their levels.

- **Development of digraph:** Here, initial digraph (also known as directed graph) is generated from CM. Digraph is developed by nodes and lines of edges.

**Step 5:** Now, develop digraph for the individual QEF category among the sub-QEF of each category (as done earlier in step 4). This is the digraph at the sub-system level.

**Step 6:** Develop VPM (sub-QEF matrix) for each QEF category.

**Step 7:** Now, substitute the value of inheritance and interdependency in sub-QEF matrix of each QEF category. For the values of inheritance, Table 7.1 should be used and for the values of interdependency, Table 7.2 should be used through proper interpretation by experts.

**Step 8:** Compute the permanent function value for each QEF category.

**Step 9:** Develop VPM (QEF matrix) at the system level.

**Step 10:** Now again, substitute the value of inheritance and interdependency in the QEF matrix at system level. In this matrix, the value of permanent function of each sub-QEF matrix provides inheritance of QEF and quantitative value of interactions among QEF is to be taken from Table 7.2.

**Step 11:** Find the permanent function value for the system. This value will deliver the decision quality index for the particular stage under consideration. Moreover, this index value i.e. PSLC-DQI mathematically illustrates the quality of decision.

**Step 12:** Find the maximum value of system by taking the maximum value (i.e. 0.9) for the inheritance at the sub-system level.
Step 13: Compare the obtained value of system with the maximum value of system. If the values are equal or nearer to the maximum value, then deploy the identified QEFs in the decision making process. If the values are much lower than the maximum value, then find the QEFs in which the present system is lacking. In such case, the organization has to identify and improve the weak links for the improvement. After the identification and improvement of weak links, compute the system value again for comparison. Repeat the same procedure, till the values come nearer or equal to the maximum value.

Step 14: Afterwards, generate the decision alternatives and select the best decision alternative by using any multi-criteria decision making approaches.

This integrated GTA-ISM methodology tries to build the quality enabled system in a particular stage of production system life cycle. In this quality enabled system, the developed decision alternatives will be of better quality.

8.2 METHODOLOGY FOR SELECTION OF BEST DECISION ALTERNATIVE

In this section, two simple but novel MCDM approaches are presented for the selection of best decision alternative. These MCDM approaches are as follows:

- MOORA approach
- PSI method

8.2.1 MOORA Approach

MOORA approach refers to the multi-objective optimization on the basis of ratio analysis. This approach is mainly used for multi-attribute optimization. Chakraborty (2011); Karande and Chakraborty (2012) have defined MOORA approach as the process of instantaneously optimizing the two or more contradictory attributes subjected to certain limits. The multi-criteria decision making problem is generally found in different stages/phases of PSLC such as product idea selection, product design selection, process design selection, facility location selection, material selection, technology selection, material handling equipment selection, employee
selection, cutting tool selection and facility layout selection etc. This approach was presented by Brauers (2004).

MOORA approach comprises of two parts viz. Ratio system approach and Reference point approach.

(a) Ratio System Approach

The steps involved in the ratio system approach are given below:

Step 1: Formulate the decision matrix:

MOORA approach starts with the creation of decision matrix comprising of performance value of various alternatives relating to different attributes.

\[
X_i = \begin{bmatrix}
X_{11} & X_{12} & X_{13} & \ldots & \ldots & X_{1N} \\
X_{21} & X_{22} & X_{23} & \ldots & \ldots & X_{2N} \\
X_{31} & X_{32} & X_{33} & \ldots & \ldots & X_{3N} \\
\vdots & \vdots & \vdots & \ddots & \ldots & \vdots \\
X_{m1} & X_{m2} & X_{m3} & \ldots & \ldots & X_{MN}
\end{bmatrix}
\]

Here, \(x_{ij}\) = performance value of \(i^{th}\) alternative pertaining to \(j^{th}\) attribute; \(m = \) number of alternatives; and \(n = \) number of attributes.

Step 2: Normalize the decision matrix:

In this step of MOORA approach, the decision matrix is normalized for making the decision matrix dimensionless. This results in the comparison of all elements of decision matrix.

Normalization of the decision matrix is carried out by using the following equation (Karande & Chakraborty, 2012):

\[
X^*_ij = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}}
\]

Here, \(X^*_ij\) = dimensionless number (in 0, 1 interval), which describes the normalized performance value.
**Step 3: Classification of attributes:**

In this step, attributes are classified into two categories viz. beneficial attribute and non-beneficial attribute. Beneficial attributes are those attributes whose greater values are essential; while non-beneficial attributes are those attributes whose lower values are essential.

**Step 4: Computation of assessment value:**

The assessment value of each alternative is calculated by the following equation:

\[
y^*_i = \sum_{j=1}^{g} X^*_{ij} - \sum_{j=g+1}^{n} X^*_{ij}
\]  \quad (8.3)

Here, \(y^*_i\) = assessment value of \(i^{th}\) alternative with regard to all the attributes, \(g\) = number of attribute to be maximized, \((n-g)\) = number of attribute to be minimized.

In equation (8.3), all the normalized performances are totalled for the beneficial attributes and deducted for the non-beneficial attributes. The assessment value can be positive or negative.

In some specific cases, attributes may be more significant than one another. To take this effect into consideration, weight of attributes is considered. The weights of attributes are generally computed by using the entropy method and AHP approach. When the weights of attributes are taken into consideration, then equation (8.3) becomes:

\[
y^*_i = \sum_{j=1}^{g} w_j X^*_{ij} - \sum_{j=g+1}^{n} w_j X^*_{ij}
\]  \quad (8.4)

Where \(w_j\) = weight of \(j^{th}\) attribute

**Step 5: Selection of best alternative:**

The alternative having the maximum assessment value is considered as the best alternative.

**(b) Reference Point Approach**

The steps involved in the reference point approach are given below:

**Step 1: Formulate the decision matrix:**
In this step, decision matrix is constructed as in the ratio system approach.

**Step 2: Normalize the decision matrix:**

Here, the decision matrix is normalized to make it dimensionless. It is normalized in the similar manner as in ratio system approach.

**Step 3: Classification of attributes:**

In this step, attributes are categorized into two categories viz. beneficial attributes and non-beneficial attributes.

**Step 4: Computation of reference point:**

In this step, a reference point is deduced from the normalized matrix. The computation of reference point depends upon the beneficial and non-beneficial attributes.

The reference point in case of beneficial attribute is the maximum value while in case of non-beneficial attribute, it is minimum value.

**Step 5: Computation of deviation from reference point:**

The deviation of an attribute value from its set reference point \( r_i \) is calculated by following equation:

\[
r_i - X_{ij}^*\]

**Step 6: Computation of performance index:**

The best alternative in the reference point approach will have maximum values in case of beneficial attributes along with the minimum values in case of non-beneficial attributes.

In practical situations, it is not likely all the times that a specific alternative will have all of the maximum values in the case of beneficial attributes and minimum values in the case of non-beneficial attributes. In such situations, there will be deviance from the reference point series. The deviation is computed by using the following equation (Karlin and Studden, 1966; Brauers and Zavadskas, 2006):

\[
P_i = \min_{(i)} \left\{ \max_{(j)} \left| r_i - X^*_{ij} \right| \right\}
\]
where \( P_i \) = performance index

**Step 7: Selection of best alternative:**

The best alternative will have the total minimum deviance from the reference point series i.e. minimum value of \( P_i \).

### 8.2.1.1 Illustrative example

For demonstrating the applicability and potentiality of MOORA approach in resolving the MCDM problem, an example of product design selection has been cited from the literature (Besharati et al., 2006). This problem is concerned with the selection of most suitable product design for a power electronic device. This problem consists of three performance attribute and ten product design alternatives. The attributes are manufacturing cost (MC), thermal cycles to failure (TCF), and junction temperature (JT), as shown in Table 8.1.

To solve the product design selection problem, the steps given underneath are carried out:

**Step 1:** Decision matrix for product design selection problem is presented in Table 8.1.

### Table 8.1: Data for product design selection problem (Besharati et al., 2006)

<table>
<thead>
<tr>
<th>Design no.</th>
<th>JT</th>
<th>TCF</th>
<th>MC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>126</td>
<td>22000</td>
<td>85</td>
</tr>
<tr>
<td>2</td>
<td>105</td>
<td>38000</td>
<td>99</td>
</tr>
<tr>
<td>3</td>
<td>138</td>
<td>14000</td>
<td>65</td>
</tr>
<tr>
<td>4</td>
<td>140</td>
<td>13000</td>
<td>60</td>
</tr>
<tr>
<td>5</td>
<td>147</td>
<td>10600</td>
<td>52</td>
</tr>
<tr>
<td>6</td>
<td>116</td>
<td>27000</td>
<td>88</td>
</tr>
<tr>
<td>7</td>
<td>112</td>
<td>32000</td>
<td>92</td>
</tr>
<tr>
<td>8</td>
<td>132</td>
<td>17000</td>
<td>75</td>
</tr>
<tr>
<td>9</td>
<td>122</td>
<td>23500</td>
<td>85</td>
</tr>
<tr>
<td>10</td>
<td>135</td>
<td>15000</td>
<td>62</td>
</tr>
</tbody>
</table>
**Step 2:** Decision matrix (Table 8.1) is normalized by using equation (8.2) as presented in Table 8.2.

**Table 8.2:** Normalized decision matrix for product design selection problem

<table>
<thead>
<tr>
<th>Design no.</th>
<th>JT</th>
<th>TCF</th>
<th>MC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0990</td>
<td>0.1037</td>
<td>0.1114</td>
</tr>
<tr>
<td>2</td>
<td>0.0825</td>
<td>0.1792</td>
<td>0.1298</td>
</tr>
<tr>
<td>3</td>
<td>0.1084</td>
<td>0.0660</td>
<td>0.0852</td>
</tr>
<tr>
<td>4</td>
<td>0.1100</td>
<td>0.0613</td>
<td>0.0786</td>
</tr>
<tr>
<td>5</td>
<td>0.1155</td>
<td>0.0500</td>
<td>0.0682</td>
</tr>
<tr>
<td>6</td>
<td>0.0911</td>
<td>0.1273</td>
<td>0.1153</td>
</tr>
<tr>
<td>7</td>
<td>0.0880</td>
<td>0.1509</td>
<td>0.1206</td>
</tr>
<tr>
<td>8</td>
<td>0.1037</td>
<td>0.0802</td>
<td>0.0983</td>
</tr>
<tr>
<td>9</td>
<td>0.0958</td>
<td>0.1108</td>
<td>0.1114</td>
</tr>
<tr>
<td>10</td>
<td>0.1060</td>
<td>0.0707</td>
<td>0.0813</td>
</tr>
</tbody>
</table>

**Step 3:** The attributes are classified into beneficial and non-beneficial attribute. Here, TCF is beneficial attribute while remaining ones are non-beneficial attributes.

**Step 4:** The assessment value \( y_i \) for each considered alternative is computed by using equation (8.4) as presented in Table 8.3.

**Table 8.3:** Ranking of alternative for product design selection problem

<table>
<thead>
<tr>
<th>Design no.</th>
<th>( P_i )</th>
<th>( y_i )</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0276</td>
<td>-0.0546</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>0.0393</td>
<td>-0.0450</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>0.0293</td>
<td>-0.0486</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>0.0305</td>
<td>-0.0458</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>0.0334</td>
<td>-0.0426</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>0.0301</td>
<td>-0.0502</td>
<td>7</td>
</tr>
<tr>
<td>7</td>
<td>0.0334</td>
<td>-0.0471</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>0.0256</td>
<td>-0.0528</td>
<td>9</td>
</tr>
<tr>
<td>9</td>
<td>0.0276</td>
<td>-0.0524</td>
<td>8</td>
</tr>
<tr>
<td>10</td>
<td>0.0280</td>
<td>-0.0446</td>
<td>2</td>
</tr>
</tbody>
</table>
Rao, (2007) solved this product design selection problem by using AHP method. Rao, (2007) determined the attribute weights as $W_{JT} = 0.1047$, $W_{TCF} = 0.2582$, and $W_{MC} = 0.6371$. Here, same weights are used for ensuing MOORA analysis.

**Step 5:** MOORA based analysis provides a ranking of 5-10-2-4-7-3-6-9-8-1 when designs are organized according to the descending order of $y_i$ values. It means that, product design number 5 is the best product design among the considered alternate designs. Besharati et al., (2006) found the ranking of design alternatives as 5-10-4-3-7-6-2-8-9-1, while Rao (2007) got ranking order as 5-4-10-2-3-7-6-8-9-1. In these two cases, product design number 5 is the best product design. So, the best alternative found by MOORA method accurately matches with that of Besharati et al., (2006) and Rao, (2007).

**8.2.2 PSI Method**

Preference selection index (PSI) method was developed by Maniya and Bhatt (2010) for solving the MCDM problems. In PSI method, there is no prerequisite of calculating the weights of attributes involved in the considered problem. This method is valuable when there is conflict in defining the relative importance between the considered attributes (Attri et al., 2014b).

Steps involved in PSI methodology are given underneath (Vahdani et al., 2011):

**Step 1: Formulate the decision matrix**

PSI method starts with the creation of decision matrix comprising of performance value of various alternatives relating to different attributes.

$$X_{ij} = \begin{bmatrix} X_{i1} & X_{i2} & X_{i3} & \ldots & X_{iN} \\ X_{j1} & X_{j2} & X_{j3} & \ldots & X_{jN} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{M1} & X_{M2} & X_{M3} & \ldots & X_{MN} \end{bmatrix}$$

(8.7)
Here, $x_{ij} =$ performance value of $i^{th}$ alternative pertaining to $j^{th}$ attribute; $m =$ number of alternatives; and $n =$ number of attributes.

**Step 2: Normalize the decision matrix**

In this step, the decision matrix (developed in step 1) is normalized to make it dimensionless. It is carried out by transforming the values of decision matrix in 0 and 1. In PSI method, normalization is done on the basis of attributes i.e. beneficial attribute or non-beneficial attribute. For this purpose, following equations are utilized:

- For beneficial attributes:
  \[
  N_{ij} = \frac{X_{ij}}{X_{j}^{\text{max}}} 
  \]  
  \(8.8\)

- For non-beneficial attributes
  \[
  N_{ij} = \frac{X_{j}^{\text{min}}}{X_{ij}} 
  \]  
  \(8.9\)

**Step 3: Compute the mean value of normalized decision matrix**

Now, mean value of the normalized decision matrix is computed by using the following equation:

\[
\bar{N} = \frac{1}{n} \sum_{i=1}^{n} N_{ij} 
\]  
\(8.10\)

**Step 4: Compute the preference variation value**

Here, preference variation value among the values of each attribute is determined by using the equation given below:

\[
\phi = \sum_{i=1}^{n} \left[ N_{ij} - \bar{N} \right]^{2} 
\]  
\(8.11\)

**Step 5: Determine deviation in preference value**

Now, deviation in the preference value for each considered attribute is determined by using equation given below:

\[
\Omega = \left[ 1 - \phi \right] 
\]  
\(8.12\)

**Step 6: Compute overall preference value**
Here, overall preference value for every considered attribute is computed by using the equation given below:

$$\omega_j = \frac{\Omega_j}{\sum_{j=1}^{m} \Omega_j}$$  \hspace{1cm} (8.13)

It may be noted here that the sum of all the preference values should be equal to one i.e. $\sum_{j=1}^{m} \Omega_j = 1$.

**Step 7: Compute preference selection index (PSI)**

At present, preference selection index (PSI) for each alternative is computed by using the equation given below:

$$\Theta_i = \sum_{j=1}^{M} X_{ij} \times \omega_j$$  \hspace{1cm} (8.14)

**Step 8: Select the best alternative**

Here, each considered alternative is ranked according to the values of PSI in descending or ascending order. The alternative having highest PSI value is considered as the best alternative.

**8.2.2.1 Illustrative example**

For demonstrating the applicability and potentiality of PSI methodology in solving the MCDM problem, an example of cutting fluid selection has been cited from the literature (Rao, 2007). This problem is concerned with the selection of appropriate cutting fluid for the cylindrical grinding. This problem consists of eight attributes and four cutting fluid alternatives. The attributes are wheel wear (WW), tangential force (TF), grinding temperature (GT), surface roughness (SR), recyclability (R), toxic harm rate (TH), environment pollution tendency (EP), and stability (S) as shown in Table 8.4. Here, R and S are the beneficial attribute and remaining ones are non-beneficial attributes.
Table 8.4: Data for cutting-fluid selection problem (Rao, 2007)

<table>
<thead>
<tr>
<th>Cutting fluids</th>
<th>WW</th>
<th>TF</th>
<th>GT</th>
<th>SR</th>
<th>R</th>
<th>TH</th>
<th>EP</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.035</td>
<td>34.5</td>
<td>847</td>
<td>1.76</td>
<td>0.335</td>
<td>0.5</td>
<td>0.59</td>
<td>0.59</td>
</tr>
<tr>
<td>2</td>
<td>0.027</td>
<td>36.8</td>
<td>834</td>
<td>1.68</td>
<td>0.335</td>
<td>0.665</td>
<td>0.665</td>
<td>0.665</td>
</tr>
<tr>
<td>3</td>
<td>0.037</td>
<td>38.6</td>
<td>808</td>
<td>2.4</td>
<td>0.59</td>
<td>0.59</td>
<td>0.41</td>
<td>0.5</td>
</tr>
<tr>
<td>4</td>
<td>0.028</td>
<td>32.6</td>
<td>821</td>
<td>1.59</td>
<td>0.5</td>
<td>0.59</td>
<td>0.59</td>
<td>0.41</td>
</tr>
</tbody>
</table>

To solve the cutting fluid selection problem, the steps given below are carried out:

*Step 1:* Decision matrix for the cutting fluid selection problem is presented in Table 8.4.

*Step 2:* Decision matrix (Table 8.4) is normalized by utilizing equations (8.8) and (8.9) as shown in Table 8.5.

Table 8.5: Normalized decision matrix for cutting-fluid selection problem

<table>
<thead>
<tr>
<th>Cutting fluids</th>
<th>WW</th>
<th>TF</th>
<th>GT</th>
<th>SR</th>
<th>R</th>
<th>TH</th>
<th>EP</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7714</td>
<td>0.9449</td>
<td>0.9540</td>
<td>0.9034</td>
<td>0.5678</td>
<td>1.0000</td>
<td>0.6949</td>
<td>0.8872</td>
</tr>
<tr>
<td>2</td>
<td>1.0000</td>
<td>0.8859</td>
<td>0.9688</td>
<td>0.9464</td>
<td>0.5678</td>
<td>0.7519</td>
<td>0.6165</td>
<td>1.0000</td>
</tr>
<tr>
<td>3</td>
<td>0.7297</td>
<td>0.8446</td>
<td>1.0000</td>
<td>0.6625</td>
<td>1.0000</td>
<td>0.8475</td>
<td>1.0000</td>
<td>0.7519</td>
</tr>
<tr>
<td>4</td>
<td>0.9643</td>
<td>1.0000</td>
<td>0.9842</td>
<td>1.0000</td>
<td>0.8475</td>
<td>0.8475</td>
<td>0.6949</td>
<td>0.6165</td>
</tr>
</tbody>
</table>

*Step 3:* Mean value of normalized data for each cutting fluid selection attribute is computed by using equation (8.10) and values are $\bar{N}_{WW} = 0.8664$, $\bar{N}_{TF} = 0.9188$, $\bar{N}_{GT} = 0.9767$, $\bar{N}_{SR} = 0.8781$, $\bar{N}_R = 0.7458$, $\bar{N}_{TH} = 0.8617$, $\bar{N}_{EP} = 0.7516$, $\bar{N}_S = 0.8139$.

*Step 4:* Preference variation value for each cutting fluid selection attribute is computed by using equation (8.11) and values are $\phi_{WW} = 0.0467$, $\phi_{TF} = 0.0139$, $\phi_{GT} = 0.0012$, $\phi_{SR} = 0.0667$, $\phi_R = 0.1383$, $\phi_{TH} = 0.0316$, $\phi_{EP} = 0.0864$, $\phi_S = 0.0828$.

*Step 5:* Deviation in the preference value for each cutting fluid selection attribute is computed by using equation (8.12) and values are $\Omega_{WW} = 0.9533$, $\Omega_{TF} = 0.9861$, $\Omega_{GT} = 0.9988$, $\Omega_{SR} = 0.9333$, $\Omega_R = 0.8617$, $\Omega_{TH} = 0.9684$, $\Omega_{EP} = 0.9136$, $\Omega_S = 0.9172$. 
Step 6: Overall preference value for each cutting fluid selection attribute is computed by using equation (8.13) and values are $\omega_{WW} = 0.1266$, $\omega_{TF} = 0.1309$, $\omega_{GT} = 0.1326$, $\omega_{SR} = 0.1239$, $\omega_{SR} = 0.1144$, $\omega_{TH} = 0.1286$, $\omega_{EP} = 0.1213$, $\omega_{S} = 0.1218$.

Step 7: Cutting fluid selection index for each cutting fluid alternative is computed by equation (8.14) and its values are $\theta_1 = 0.8457$, $\theta_2 = 0.8465$, $\theta_3 = 0.8539$, $\theta_4 = 0.8727$.

Step 8: Cutting fluid alternatives are organized in descending order on the basis of PSI as $\theta_4 > \theta_3 > \theta_2 > \theta_1$.

The PSI based analysis reveals that fourth cutting fluid is the best cutting fluid for the considered cylindrical grinding operation. Rao, (2007) also found the fourth cutting fluid as the best cutting fluid by using GTA approach. So, results obtained by PSI method exactly matches with that of Rao, (2007).

### 8.3 CONCLUDING REMARKS

- Manufacturing organizations are facing the problem of selecting the best decision alternatives in the present era of cut-throat competition.
- Moreover, this developed methodology can be utilized in all stages of production system life cycle.
- The suggested integrated methodology offers a general procedure that can be utilized for the selection of best decision alternative consisting of numerous alternatives and attributes.