CHAPTER 5

A FUZZY VECTOR MODEL TO MEASURE THE ROBOT PERFORMANCE
in the past few years, but still an efficient algorithm is to be developed to measure the performance.

5.2 LITERATURE SURVEY

A paper by Kapoor and Tak [45] has reported some important technique to address the problem of robot selection and contains a good number of references. However, overview of these methods are given below:

In multi attribute decision making models, all objectives of the decision maker are unified under a super function which is termed as the decision's maker's utility, which depends on robot attributes.

In another approach such as optimal utilization of resources and improved quality are assigned weights reflecting their relative importance. Production system performance optimization model is based on optimization of some performance measure of the production system such as quality. Computer assisted models as proposed by OFFODILE O F et al [78] used an expert system to evaluate a large number of robot engineering attributes from the available data base and provides a feasible list of robots.

Hinson R [37] has considered the environment, as a major factor in robot selection. He suggested that ambient condition where the robot is going to operate should be specified by the manufactures.

Philip Y Huang [44] gave procedure for evaluating and selecting robots based on criteria factors, such as objective factors and subjective factors. He
5.5 FUZZY LINGUISTIC VARIABLE

A "Fuzzy Linguistic Variable" is an expression, which represents a variety of values, for example, "age", is a Linguistic Variable, if it has non numerical value such as young, not young, very young, old, very old etc. The Linguistic Variables are assumed to be spread over the "Universe of Discourse" by means of overlapping triangular or any other geometric representation. In the present chapter Linguistic Values from Term Set (very low, low, medium, high and very high) are used to explicate the Fuzzy Linguistic Variable "preference" Linguistic Variable from the Term Set (very poor, poor, fair, good, very good) are employed to explicate "suitability."

The use of "crisp" numerical values for quantification of subjective opinions, the concepts of "Fuzzy Linguistic Variables" provides us with a convenient means of making subjective judgments about complex situations.

5.6 THE PROBLEM STATEMENT

The problem of robot selection posses the following challenges:

1. Wide spectrum of options is available to the robot users.

2. The parameter of the selections changes with the context. Most criteria influencing the performance have an element of Fuzziness.

3. All the parameters are not of equal importance for any activity. These parameters may be of essential or desirable type.
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$L = [0.05, 0.20, 0.25, 0.3, 0.4]$

$M = [0.25, 0.40, 0.45, 0.6, 0.65]$

$H = [0.50, 0.65, 0.70, 0.8, 0.9]$

$VH = [0.75, 0.8, 0.9, 1.05, 1.0]$

By representing the discrete membership functions of the Linguistic Values with $\mu_T(x)/x$, where $\mu_T(x)$ is the membership grad of point $x$, we have,

$\mu_M = [0.25, 0.40, 0.45, 0.5, 0.65]$

The minimum operator, which usually represents, the intersection of Fuzzy Sets, does not allow for any compensation among these sets. From e.g. if the connective "AND" is represented by the minimum operator in the statement "high AND low" then $\mu_{H \text{AND} L}(X) = \mu_{H \cap L}(X) = 0$ which does not reflect the way of merging the information of given value where as, it has been explained logically earlier and the author has considered that the "AND" connective in the expert rules should take values between those given by the classical intersection and union. By taking the convex combination of the union $U$ and intersection $\cap$ for the antecedent of (IF-THEN), we have

$\mu_{H \text{AND} L}(X) = (1-\gamma) \mu_{H \cap L}(X) + \gamma \mu_{U \cap L}(X)$ where $x \in X, \gamma \in (0,1)$

Where $\gamma$ is the grade of compensation and indicates where the actual operator is located between the classical union (full compensation, $\gamma=1$) and intersection (no compensation $\gamma=0$) of the connected sets, [133]. Intersection and Union are represented by the minimum ($=\cap$) and maximum ($=U$) operators respectively.

For example,
High (H) = [0.50, 0.65, 0.70, 0.8, 0.9]
Low (L) = [0.05, 0.20, 0.25, 0.40, 0.45]

Taking $\gamma = 0.4$, we have,

$\text{HAND L} = [0.23, 0.38, 0.43, 0.56, 0.63]$

Where, for instance, the value $(0.43) = [(1-0.4)(0.70\cap0.25)+0.4(0.70\cup0.25)]$

5.8 CONCEPT

Every attribute of the robot can be assigned a fuzzy number in the scale 0 to 1. It is easy to see that the full quantified attributes (if possible) will have a crisp number (1) assigned to it.

The crisp number zero (0) in the scale represent a parameter of attributes isolated from the prediction while another crisp number one (1) means that the attribute is fully explained or quantified.

For robot selection, in general, both the crisp numbers cannot exist and the practically attributes may have fuzzyness i.e. they may have intermediate values.

Obvious the parameters with fuzzy values such as 0.6, 0.4 indicates possible contribution for the function among robots but to what extent they will have the contribution in the performance is uncertain. In order to know the mobility of attributes/parameters of a robot, we can use make of "entropy" which is a measure of uncertainty.
Entropy of a fuzzy vector is defined as the ratio of

\[ \frac{||X-P||}{||X-N||} \quad (5.1) \]

Where \( P \) is the nearest and \( N \) the farthest crisp vector from \( X \).

Following criteria and steps will be followed as described below:

**Step-I DEFINING INPUTS AND OUTPUTS FOR THE ROBOTS PERFORMANCE**

The range of values that inputs and outputs may take is called Universe of discourse. We need to define the universe of discourse for all of the inputs and outputs of the fuzzyness, which all crisp values as explained above.

**Step-II FUZZIFY THE INPUTS**

The inputs to the robot selection may be velocity repeatability and or load capacity. We can use triangular membership functions to fuzzify the inputs.

**Step-III CREATE A FUZZY RULE BASE (MODELING & MEASUREMENT OF PERFORMANCE)**

The main idea of use of this model is the involvement of all the related parameter of a robot to know its ability to perform the required task compared to that of another robot. This is implemented via multi-antecedent fuzzy (IF-THEN rules). These rules are conditional statements that relate the observation concerning the allocated types (Velocity and repeatability and load capacity) [IF-part] with the value of performance (THEN-part). An example of such a rule is, if the velocity is medium AND repeatability is very high AND load capacity is medium, then performance will be medium.
Step-IV  DEFUZZIFY THE OUTPUTS

After getting the IF-THEN of the fuzzy rule base at once, the inputs have been fuzzified. How do we arrive at a single crisp output vector. The criteria proposed to quantify performance are explained below. Consider three fuzzy vectors A, B, and C as explained above, from the same space. It is possible to consider one vector as a subset of the other vector. It is necessary to establish the extent to which vector B is a subset of A and vice-versa. The following expressions can be used to know the membership of one set within another. The minimum operator, which usually represents, the intersection of Fuzzy Sets, does not allow for any compensation among these sets. From e.g, if the connective "AND" is represented by the min. operator in the statement "high AND low" then $\mu_{H \text{ AND } L}(X) = \mu_{H \cap L}(X) = 0$ which does not reflect the way of merging the information of given value where as, it has been explained logically earlier and the author has considered that the "AND" connective in the expert rules should take values between those given by the classical intersection and union. By taking the convex combination of the union $U$ and intersection $\cap$ for the antecedent of (IF-THEN), we have

$$\mu_{H \text{ AND } L}(x) = (1-\gamma) \mu_{H \cap L}(x) + \gamma \mu_{H \cup L}(x) \text{ where } x \in X, \gamma \in (0,1) \quad (5.2)$$

Where $\gamma$ is the grade of compensation and indicates where the actual operator is located between the classical union (full compensation, $\gamma=1$) and intersection (no compensation $\gamma=0$) of the connected sets [133]

For example,

High (H) = [0.50, 0.65, 0.70, 0.8, 0.9]

Low (L) = [0.05, 0.20, 0.25, 0.40, 0.45]
Taking $\gamma = 0.4$, we have,

$H = \{0.23, 0.38, 0.43, 0.56, 0.63\}$

Where, for instance $0.43 = [(1-0.4)(0.70 \cap 0.25) + 0.4(0.70 \cup 0.25)]$

### 5.9 MEASUREMENT OF PERFORMANCE

As explained earlier, the entropy, which is measure of uncertainty, can be used to quantify the performance.

Let criterion performance be taken to depend on three sub criteria viz Velocity (V), Repeatability (R), and Load capacity (LC). Let the procedure laid out in the previous stages be repeated for evaluation of preference of V, R and LC with respect to performance (P). Using linguistic variables from the set \{VL, L, M, H, VH\} and let the observations by expertise may be considered as shown in Table 5.1

<table>
<thead>
<tr>
<th>Criterion</th>
<th>$R_1$</th>
<th>$R_2$</th>
<th>$R_3$</th>
<th>$R_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Velocity</td>
<td>Medium (M)</td>
<td>Medium (M)</td>
<td>Low (L)</td>
<td>High (H)</td>
</tr>
<tr>
<td>Repeatability</td>
<td>Very High (VH)</td>
<td>High (H)</td>
<td>Very High (VH)</td>
<td>Medium (M)</td>
</tr>
<tr>
<td>Load Capacity</td>
<td>Medium (M)</td>
<td>Medium (M)</td>
<td>Medium (M)</td>
<td>Low (L)</td>
</tr>
</tbody>
</table>

**Case-1 For robot $R_1$:**

The observation is

$O \rightarrow [M, VH, M]$  

The membership functions M, VH, M are

$M = [0.25, 0.40, 0.45, 0.6, 0.65]$
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\[ \text{VH} = [0.75, 0.8, 0.9, 1.0, 1.0] \]
\[ \text{M} = [0.25, 0.40, 0.45, 0.6, 0.65] \]

The discrete membership of the observation \( o \) is \( \text{M} \) and \( \text{VH} \) and \( \text{M} \).

Using eq (5.2), taking \( \gamma = 0.4 \), we have

\[ \mu_{\text{M} \text{ and VH}}(x) = [0.45, 0.56, 0.63, 0.76, 0.79] \]

and therefore the fuzzy vector \( x \) is

\[ \mu_{\text{M} \text{ and VH}}(x) = [0.33, 0.464, 0.522, 0.664, 0.706] \]

Using the entropy equation, we have its nearest crisp vector \( p \) is \([0, 0, 1, 1, 1, 1, 1]\).

The nearest distance is

\[ (X-P) = [ (0.33) + (0.464) + (1-0.522) + (1-0.664) + (1-0.706)] \]
\[ = 1.902 \]

The farthest crisp vector \( M \) is \([1, 1, 0, 0, 0, 0]\).

The farthest distance is

\[ (X-N) = [ (1-0.33) + (1-0.464) + (0.522) + (0.664) + (0.706)] \]
\[ = 0.67 + 0.536 + 0.522 + 0.664 + 0.706 \]
\[ = 3.098 \]

The performance entropy is \( 1.902/3.098 = 0.6139 \).

**Case II** For robot \( R_2 \).

The observation is

\[ O \rightarrow [\text{M}, \text{H}, \text{M}] \]

The membership functions \( \text{M}, \text{H}, \text{M} \) are

\[ \text{M} = [0.25, 0.40, 0.45, 0.6, 0.65] \]
\[ \text{H} = [0.50, 0.65, 0.70, 0.80, 0.90] \]
\[ \text{M} = [0.25, 0.40, 0.45, 0.6, 0.65] \]
The discrete membership of the observation $O$ is $M$ and $H$ and $M$

Using eq (5.2), taking $\gamma = 0.4$, we have

\[ \mu_{M \text{ and } H}(x) = [0.35, 0.50, 0.55, 0.68, 0.75] \]

and therefore the fuzzy vector $x$ is

\[ \mu_{M \text{ and } H \text{ and } M}(x) = [0.29, 0.44, 0.49, 0.632, 0.69] \]

Using the entropy equation, we have its nearest crisp vector $p$ is $[0, 0, 0, 1, 1]$

The nearest distance is

\[(X-P) = [(0.29) + (0.44) + (0.49) + (1-0.632) + (1-0.69)]
= 1.898\]

The farthest crisp vector $N$ is $[1, 1, 1, 0, 0]$

The farthest distance is

\[(X-N) = [(1-0.29) + (1-0.44) + (1-0.49) + (0.632) + (0.69)]
= 3.102\]

The performance entropy is

\[= 1.898/3.102 = 0.6118\]

CASE-III FOR ROBOT R3 the observation is

$\mu = [L, VH, M]$

The membership functions for $L$, $VH$, and $M$ are

$L = [0.05, 0.20, 0.25, 0.3, 0.4]$

$VH = [0.75, 0.8, 0.90, 1.05, 1.0]$

$M = [0.25, 0.40, 0.45, 0.6, 0.65]$

The discrete membership of the observation $O$ is $L$ and $VH$ and $M$

Using eq (5.2), taking $\gamma = 0.4$, we have
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\[ \mu_{\text{ANDVH}}(x) = [0.33, 0.44, 0.51, 0.56, 0.64] \]

Therefore \[ \mu_{\text{LAND AND VH AND M}}(x) = \{(1-0.4) \ 0.33 \cap 0.25 \} + 0.4(0.33 \cup 0.25) \]
\[ \{(1-0.4) \ 0.44 \cap 0.40 \} + 0.4(0.44 \cup 0.4) \]
\[ \{(1-0.4) \ 0.51 \cap 0.45 \} + 0.4(0.51 \cup 0.45) \]
\[ \{(1-0.4) \ 0.58 \cap 0.6 \} + 0.4(0.58 \cup 0.6) \]
\[ \{(1-0.4) \ 0.64 \cap 0.65 \} + 0.4(0.64 \cup 0.65) \]

The fuzzy vector \( x \) is \[ [0.282, 0.416, 0.474, 0.588, 0.644] \]

Using the entropy vector equation \[ ||X-P|| \] / \[ ||X-N|| \], we have its nearest crisp vector \( P \) is

\[ [0, 0, 0, 1, 1] \]

Hence the nearest distance is

\[ ||X-P|| = [(0.282) + (0.416) + (0.474) + (1-0.568) + (1-0.644)] = 1.96 \]

Farthest crisp vector \( N \) is

\[ [1, 1, 1, 0, 0] \]

The farthest distance is

\[ ||X-N|| = [(1-0.282) + (1-0.416) + (1-0.474) + (0.568) + (0.644)] \]
\[ = [0.718 + 0.584 + 0.526 + 0.588 + 0.844] \]
\[ = 3.06 \]

Therefore, the performance entropy of the: \( 1.96 / 3.06 = 0.64 \)

Case-IV For robot \( R_4 \), the observation is \( \mu_T = [H, M, L] \)

The membership function for \( H, M, L \) is

\[ H = [0.50, 0.65, 0.70, 0.8, 0.90] \]
\[ M = [0.25, 0.40, 0.45, 0.6, 0.65] \]
\[ L = [0.05, 0.20, 0.25, 0.3, 0.4] \]

The discrete membership of the observation \( O \) is \( H \) and \( M \) and \( L \)

Using eq (5.1), taking \( \gamma = 0.4 \), we have
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\( \mu_{H} \) and \( \mu_{L}(x) = [0.35, 0.50, 0.55, 0.68, 0.75] \)

Therefore the fuzzy vector \( x \) is \( \mu_{H} \) and \( \mu_{L}(x) = [0.17, 0.32, 0.37, 0.452, 0.54] \)

\[ 0.17, 0.32, 0.37, 0.452, 0.54 \]

Using the entropy equation, we have its nearest crisp vector \( p \) is \([0,0,0,0,1]\)

Therefore \((X-P) = [(0.17) + (0.32) + (0.37) + (0.452) + (1-0.54)] \)

\[ = 1.772 \]

Farthest crisp vector \( N \) is \([1, 1, 1, 1, 0]\)

Therefore \((X-N) = [(1-0.17) + (1-0.32) + (1-0.37) + (1-0.452) + (0.54)] \)

\[ = 0.83 + 0.68 + 0.63 + 0.55 + 0.54 \]

\[ = 3.23 \]

The performance entropy is \( 1.772 / 3.23 = 0.548 \)

Hence the single value of membership function of performance generated by four robots can be tabulated as

<table>
<thead>
<tr>
<th>Robot</th>
<th>Performance Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.6139</td>
</tr>
<tr>
<td>2</td>
<td>0.6118</td>
</tr>
<tr>
<td>3</td>
<td>0.64</td>
</tr>
<tr>
<td>4</td>
<td>0.548</td>
</tr>
</tbody>
</table>

The above result reveals that the robot 3 has largest entropy of 0.64 and hence can be delivered better performance followed by robot 1 having entropy 0.6139.
5.10 CONCLUSIONS

In this work, knowledge based framework for the assessment of performance has been presented. The measure incorporates certain robot attribute parameters (such as velocity, repeatability and load capacity). The methodology put forward in this chapter is an improvement over conventional techniques as it can even solve those problems, which are based on subjective parameters. It allows the evaluator, the freedom to express his views in words or phrases as against number. The necessary expertise is represented via fuzzy logic terminology, which has human knowledge representation and reasoning. The concept of fuzzy entropy is applied in order to measure the robotic performance. Higher the entropy better is the performance.
CHAPTER 6

ENTROPY BASED QUALITY MEASUREMENT OF ROBOT