FUZZY BASED DECISION MAKING FOR SELECTION OF FLUID FILM JOURNAL BEARING

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ABSTRACT
This paper presents a theoretical prediction of selection procedure for fluid film journal bearing by incorporating fuzzy approach. In this paper a fuzzy model is proposed for selection of hydrostatic, hydrodynamic and hybrid journal bearing. Selection criteria is formulated for the choice of space requirement, total cost of bearing and load bearing capacity of the related journal bearing. This method provides a third dimension to the existing method of selection of bearing, which is dynamic and may be further refined to address every individual needs. Therefore a fuzzy logic approach is used for decision making for selection of correct fluid film bearing.

KEYWORDS
Fluid film journal bearing, fuzzy logic, expert system.

1. INTRODUCTION

Bearing are machine elements that permits relative motion of two parts in one or more directions with a minimum of friction while preventing motion in the direction of applied load. Fluid film bearings are classified according to the manner in which load is supported, viz., hydrodynamic, hydrostatic and hybrid. The past conventional hydrostatic journal bearing were restricted to support heavy load at zero or low speed and also at low eccentricity required for precision machine. And also limitation of poor performance of hydrodynamic bearings at low speed compelled the designers to improve the performance of hydrostatic journal bearings and to develop alternative configurations in order to meet expanding industrial demands at different speeds. Therefore the hybrid journal bearings have been developed and used successfully in machines, which operates under high speed and heavy load conditions. A hybrid bearing combines the physical mechanisms of both hydrodynamic and hydrostatic bearings. An advantage of hybrid bearing over purely hydrostatic bearings is the ability to tolerate substantial loads over and above the normal design load. Also these bearings have advantages for withstanding heavy dynamic loadings which vary widely in the direction of rotation. An important feature of a selection procedure for fluid film bearings is the strategy for selecting the bearing type and configuration, its fluid feeding control devices. These basic decisions are usually made or considered at early stage of the design process [5]. Many researchers have discussed the advantages of hydrostatic, hydrodynamic and hybrid bearings in their research work [9-14].

Fuzzy logic was first proposed by Zadeh L.A. [1] of the University of California at Berkeley in a paper. He has elaborated his ideas in 1973 through a research work that introduced the concept of
"linguistic variables", which in this article equates to a variable defined as a fuzzy set. Other research followed, by the first industrial application, a cement kiln built in Denmark.

Why Use Fuzzy Logic?

Here is a list of general observations about fuzzy logic:
- Fuzzy logic is conceptually easy to understand.
- Fuzzy logic is flexible.
- Fuzzy logic is tolerant of imprecise data.
- Fuzzy logic can model nonlinear functions of arbitrary complexity.
- Fuzzy logic can be built on top of the experience of experts.
- Fuzzy logic can be blended with conventional control techniques.
- Fuzzy logic is based on natural language.

The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic.

The last statement is perhaps the most important one and deserves more discussion. Natural language, that which is used by ordinary people on a daily basis, has been shaped by thousands of years of human history to be convenient and efficient. Sentences written in ordinary language represent a triumph of efficient communication. We are generally unaware of this because ordinary language is, of course, something we use every day. Since fuzzy logic is built atop the structures of qualitative description used in everyday language, fuzzy logic is easy to use.

Fuzzy has enabled researchers to quantify data which is generic in nature. Until now generic information cannot be measured. How will you decide how worthwhile it will be visiting a food joint? Good food, great place, nice offer are just not sufficient to help you in taking a decision, unless you have a scale to measure how good, how much nice etc. Unless information or data is precise we cannot work on it or utilize it. People interact among themselves through natural language which exists in numerous variations, but when they try to interact with machines and systems, they encounter vague and imprecise concepts which are easy to understand but difficult to interpret. For example the statement "Temperature today is 38°C." does not explicitly state that today it’s hot, and the statement "Today’s temperature is 1.2 standard deviations about the mean temp for daytime in the month of May." is fraught with difficulties: would a temp 1.1999999 standard deviations above the mean be hot?[2, 6, 7]

In this paper, the development of a fuzzy based selection strategy is described for fluid film journal bearing. Fuzzy set theory thus aims at modeling imprecise, vague and fuzzy information. Computers cannot adequately handle such problems, because machine intelligence still employs sequential (Boolean) logic. The superiority of the human brain results from its capacity of handling fuzzy statements and decisions, by adding to logic parallel and simultaneous information sources and thinking processes, and by filtering and selecting only those that are useful and relevant to its purposes. The strategy includes the design of expert system, selection of membership function, input, output and a fuzzy rule base. The selection strategy has been implemented on the selection of fluid film bearing in this paper with one example also.

2. EXPERT SYSTEM: AN OVERVIEW

In ordinary Boolean algebra, an element is either contained or not contained in a given set. Fuzzy sets describe sets of elements or variables where limits are ill-defined or imprecise, the transition between membership and Non-membership is gradual, and an element can "more or less" belong to a set consider for instance the set of "costly bearing". In Boolean algebra, it is assumed that any
individual bearing either belongs or does not belong to the set of costly bearing. This implies that the individuals will move from the category of "costly bearing" to the complementary set of "cheep bearing".

Fuzzy set theory allows for grades of membership. Depending on the specific application, one might for instance decide that bearing of cost more than Rupees 20 lakhs under definitely costly, while bearing having cost below Rs 1000 is definitely not costly, and that a bearing having cost Rs. 10,000 is "more or less" costly, or is costly with a grade membership of 0.3, on a scale from 0 to 1.

2.1. Methodology

The fuzzy logic expert system for selecting correct bearing, the following three input is taken for consideration i.e. index of cost of bearing, space required for bearing, load bearing capacity” concept. This index reflects the degree of vagueness in cost or elusiveness in the information furnished by the vendor and the information collected by the designer from various other sources. Fuzzy logic is a very powerful tool for dealing with human reasoning and decision making processes which involve ambiguity, approximation, inaccuracy, inexactness, inexact information, perception, qualitativeness, subjectivity, uncertainty, vagueness or sources of imprecision that are non-statistical in nature. By applying fuzzy logic, one can quantify the contribution of a set of information to various parameters in terms of fuzzy membership. During the past few decades, fuzzy logic has used as an attractive tool for various applications ranging from household goods, finance, traffic control, automobile speed control, nuclear reactor, and earthquake detections etc.

2.2. System Architecture

![Figure 1 Fuzzy expert System](image)

Here develop a fuzzy logic based expert system for selection of correct fluid film bearing. Figure 1 shows the control mechanism of such system. The fuzzy logic based expert system consists of four components: fuzzifier, inference engine, defuzzifier, and the rule base. The role of fuzzifier is to convert a crisp input variable into linguistic variables. That is ready to be processed by the inference engine. The inference engine using the fuzzified inputs and the rules stored in the rule base process the incoming data and produces linguistic output. Once the output linguistic values are available, the defuzzifier produces the final crisp values from the output linguistic values. The validation process starts by entering two sets of data; one furnished by the vendor and the other obtained by the designer reviewing the demand. This information is obtained from a
standard design data catalogue form that is used by the designer. This form contains different sections, each section containing a set of information such as budget of company, available space of installation, load bearing requirement, type of machine in which bearing is installed e.g. pump, turbine etc. All the requirements are try to fulfill if the output values are below to a certain value. These qualitative measures are quantified and converted into linguistic variables with corresponding membership functions.

\[
X_i = \frac{\sum_{j=1}^{I} \sum_{j=1}^{J} W_{ij} \Delta_{ij}}{I}
\]

Where \( W_{ij} \) is the weightage or impact factor given to the \( j^{th} \) information of the \( i^{th} \) section, and \( \Delta_{ij} \) is a 0-1 variable (\( \Delta_{ij} = 1 \) if there is any deviation/difference in the information furnished by the vendor and the one obtained by the designer, 0 otherwise). It is worthwhile noting that the information that is crucial in decision making of selection of bearing is given higher weightage/impact factor. Also all the weights for a set of \( i^{th} \) information, \( \sum_{j=1}^{J} W_{ij} \) added to unity.

Similarly, the values of the other inputs can be determined. The normalized values of these measures are used as inputs to the expert system. The degree of membership corresponding to a value of input is determined by the use of triangular membership functions because of their simplicity and good result obtained by simulation. These membership functions are designed on the basis of available information.

Figure 2 shows the definition of the fuzzy sets of the input and the output functions. A rule base is then constructed which will based on all the applicable input parameters and for each decision several rules are to be fired. Table 1 shows a sample rule base for the system under consideration which emphasize on the fact that in real life situations

The output of expert system is defuzzified on the basis of power ratio. Power ratio is the ratio of friction power and pumping power. It is denoted by \( K \).

- \( 1 \leq K \leq 3 \) Hydrostatic bearing (Recess bearing)
- \( 3 \leq K \leq 12 \) Hybrid bearing (Non recessed bearing)
- \( 12 \leq K \leq 40 \) Hydrodynamic bearing

Power ratio \( (K) = \frac{H_f}{H_p} \)

Where \( H_f = \text{friction power } (\mu A_f U^2/h_0) \), \( H_p = \text{pumping power } (H_p = P_s \cdot q) \)
**Figure 2** Membership functions of inputs and outputs functions

<table>
<thead>
<tr>
<th>Rule No</th>
<th>X₁ (I/P)</th>
<th>X₂ (I/P)</th>
<th>X₃ (I/P)</th>
<th>Y (O/P)</th>
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Where X₁ (I/P) cost of bearing, X₂ (I/P) Space required for bearing, X₃ (I/P) Load carrying capacity, Y (O/P) power ratio
3. ALGORITHMS USING FUZZY APPROACH

The steps of the expert system are summarized below:

1. **Input.** The crisp value of the cost of bearing, space required for bearing, load carrying capacity and other information obtained in the normalized form.

2. **Evaluate the main parameter.** Determine the cost of bearing index $X_1$, space requirement for bearing $X_2$, load bearing capacity $X_3$.

3. **Fuzzify the crisp values of inputs.** Through the use of membership functions defined for each fuzzy set for each linguistic variable (Figure 2), determine the degree of membership of a crisp value in each fuzzy set. Each of these three ambiguity indices have been divided into three fuzzy sets (LOW – L, MEDIUM – M and HIGH – H). The equations for computing memberships are:

   \[
   \mu(X_i)_{L} = \max \left\{ \frac{X_i - a_i^L}{c_i^L - a_i^L} \right\} \quad \text{if} \quad c_i^L \leq X_i
   \]

   \[
   \mu(X_i)_{M} = \max \left\{ \frac{0}{c_i^M - a_i^M} \right\} \quad \text{if} \quad c_i^M \leq X_i
   \]

   \[
   \mu(X_i)_{H} = \max \left\{ \frac{X_i - a_i^H}{c_i^H - a_i^H} \right\} \quad \text{if} \quad c_i^H \leq X_i
   \]

where $(a, c, b)$ are the vertices of the triangular membership function while L, M and H represents the fuzzy set LOW, MEDIUM, and HIGH, respectively.

4. **Fire the rule bases that correspond to these inputs.** All expert systems which is based on fuzzy logic uses IF-THEN rules. The “IF” part is known as antecedent or premise, whereas the “THEN” part is termed as a consequence or conclusion. Since all the three inputs have three fuzzy sets (LOW – L, MEDIUM – M and HIGH – H) therefore 27 (3x3x3) fuzzy decisions are to be fired. There are three outputs: Hydrostatic (HY), Hybrid (HD) and Hydrodynamic bearing (HD).

5. **Execute the inference engine.** Once all crisp input values have been fuzzified into their respective linguistic values, the inference engine will access the fuzzy rule base of the fuzzy expert system to derive linguistic values for the intermediate as well as the output linguistic variables. The two main steps in the inference process are aggregation and composition. Aggregation is the process of computing the values of the IF (antecedent) part of the rules while composition is the process of computing the values of the THEN (conclusion) part of the rules. During aggregation, each condition in the IF part of a rule is assigned a degree of truth based on the degree of membership of the corresponding linguistic term. From here, product (PROD) of the degrees of truth of the conditions are computed to clip the degree of truth from the IF part. This is assigned as the degree of truth of the THEN part. The next step in the inference process is to determine the degrees of truth for each linguistic term of the output linguistic variable. Usually, either the maximum (MAX) or sum (SUM) of the degrees of truth of the rules with the same linguistic terms in the THEN parts is computed to determine the degrees of truth of each linguistic term of the output linguistic variable.

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6. **Defuzzification.** The last phase in the fuzzy expert system is the defuzzification of the linguistic values of the output linguistic variables into crisp values. The most common techniques for defuzzification are center-of-maximum (CoM) and center-of-area (CoA). CoM first determines the most typical value for each linguistic term for an output linguistic variable, and then computes the crisp value as the best compromise for the typical values and respective degrees of membership. The other common method, CoA, or sometimes called center-of-gravity (CoG), first cuts the membership functions of each linguistic term at the degrees corresponding to the linguistic values. The superimposed areas under each cut membership function are balanced to give the compromised value. A disadvantage of this technique is the high computational demands in computing the areas under the membership functions. There are other variants of computing crisp values from linguistic values. These are mean-of-maximum (MoM), left-of-maximum (LoM) or smallest-of-maximum (SoM), right-of-maximum (RoM) or largest-of-maximum (LoM), weighted average (WA) and bisector-of-area (BoA) [7].

7 **Output of the decisions of the expert system.** In this case, the types of the outputs are: hydrostatic, hybrid bearing and hydrodynamic bearing. This selection is based on power ratio factor. The specific features of each controller depend on the model and performance measure. However, in principle, in all the fuzzy logic based expert system, we explore the implicit and explicit relationships within the system by mimicking human thinking and subsequently develop the optimal fuzzy control rules as well as knowledge base.

**Example:** For the purpose of illustration, Authors consider that a power generation company requires a fluid film bearing to support the turbine shaft and they provided three inputs as desired in fuzzy expert system. i.e. budget for bearing purchase is around Rs. 20 lakhs (cost of bearing)X₁, total area available for installation of bearing unit is approximately 70 m² X₂ and weight of turbine shaft is 500 kgf. X₃. These inputs represent the degree of vagueness/doubt in the information furnished during various time periods. The degree of vagueness/doubt in the information and the level of judgment used by the vendor as well as designer in deciding the type of bearings are always a challenge. At this type of situation fuzzy based expert system is a very good tool for decision making for both vendor as well as customers.

(1) First normalized all three inputs by dividing max value of corresponding input to the given input by the customer.

(2) Evaluate the authenticity. The values of the inputs have to be evaluated in fuzzy form, X₁ = 0.40; X₂ =0.70 and X₃ = 0.50 (say).

(3) Fuzzification of the crisp values of inputs. Through the use of membership functions defined for each fuzzy set for each linguistic variable (Figure2), the degree of membership of a crisp value in each fuzzy set is determined as follows:

\[
\begin{align*}
\mu(X_1)_L &= \max\left\{0, \frac{b^L - X_1}{b^L - c^L}\right\} = 0.22 \\
\mu(X_1)_M &= \max\left\{0, \frac{X_1 - a^M}{c^M - a^M}\right\} = 0.25 \\
\mu(X_1)_H &= \max\left\{0, \frac{X_1 - a^H}{c^H - a^H}\right\} = 0
\end{align*}
\]

\[
\begin{align*}
\mu(X_2)_L &= \max\left\{0, \frac{b^L - X_2}{b^L - c^L}\right\} = 0.25 \\
\mu(X_2)_M &= \max\left\{0, \frac{X_2 - a^H}{c^H - a^H}\right\} = 0.667
\end{align*}
\]
\[
\mu(X_3)_L = \max \left\{ 0, \frac{b^L_3 - X_3}{b^L_3 - c^L_3} \right\} = 0 \quad \mu(X_3)_M = \max \left\{ 0, \frac{b^M_3 - X_3}{b^M_3 - c^M_3} \right\} = 1
\]

\[
\mu(X_3)_H = \max \left\{ 0, \frac{X_3 - a^H_3}{c^H_3 - a^H_3} \right\} = 0
\]

where

\[
\begin{align*}
(a^L_1, c^L_1, b^L_1) &= (0, 0.225, 0.45); \\
(a^M_1, c^M_1, b^M_1) &= (0.35, 0.55, 0.75); \\
(a^H_1, c^H_1, b^H_1) &= (0.55, 0.775, 1.0) \\
(a^L_2, c^L_2, b^L_2) &= (0, 0.225, 0.45); \\
(a^M_2, c^M_2, b^M_2) &= (0.35, 0.55, 0.75); \\
(a^H_2, c^H_2, b^H_2) &= (0.55, 0.775, 1.0) \\
(a^L_3, c^L_3, b^L_3) &= (0, 0.225, 0.45); \\
(a^M_3, c^M_3, b^M_3) &= (0.45, 0.50, 0.55); \\
(a^H_3, c^H_3, b^H_3) &= (0.55, 0.775, 1.0)
\end{align*}
\]

(5)

Fire the rule bases that correspond to these inputs. Based on the value of the fuzzy membership function values for the example under consideration, the following rules apply:

Rule 5: If \(X_1\) is LOW, \(X_2\) is MEDIUM, \(X_3\) is MEDIUM then \(Y\) is a Hydrostatic bearing (HS).
Rule 8: If \(X_1\) is LOW, \(X_2\) is HIGH, \(X_3\) is MEDIUM then \(Y\) is a Hybrid bearing (HY).
Rule 14: If \(X_1\) is MEDIUM, \(X_2\) is MEDIUM, \(X_3\) is MEDIUM then \(Y\) is a Hydrostatic bearing (HS).
Rule 17: If \(X_1\) is MEDIUM, \(X_2\) is HIGH, \(X_3\) is MEDIUM then \(Y\) is a Hybrid bearing (HY).

(4) Execute the Inference Engine. We use the “root sum squares” (RSS) method to combine the effects of all applicable rules, scale the functions at their respective magnitudes. The respective output membership function strengths (range: 0-1) from the possible rules (R1-R27) are:

\[
\text{“Hydrostatic bearing index”} = \sqrt{\sum_{i \in AS} (\mu_{R_i})^2} = \sqrt{(0.22)^2 + (0.25)^2} = 0.33
\]

\[
\text{“Hybrid bearing index”} = \sqrt{\sum_{i \in SF} (\mu_{R_i})^2} = \sqrt{(0.22)^2 + (0.25)^2} = 0.33
\]

66
Defuzzification. In this paper “fuzzy centroid algorithm” is used for defuzzification. The defuzzification of the data into crisp output is accomplished by combining the results of the inference process and then computing the “fuzzy centroid” of the area. The weighted strengths of each output member function are multiplied by their respective output membership function center points and summed. Finally, this area is divided by the sum of the weighted member function strengths and the result is taken as the crisp output.

Output of the decisions of the expert system. From Figure 3, it is concluded that the bearing should be hybrid bearing because the power ratio of the bearing is 6.5.

4. CONCLUSION

The use of a fuzzy based expert system for selection of bearing is taken into consideration by the author. Our future efforts will be on the improvement of the performance of the system by taking the trapezoidal membership function of the inputs. It would be interesting to tune the rule base using data from real life problems so that the performance of the system is optimized. It is proposed to use neural networks that can produce an optimum surface representing all the combination points from a few of the tested combinations. It is worthwhile noting that inclusion of these factors would increase the size of the rule base to the point that the tuning of the rule base using data from real life scenarios will be deemed necessary to optimize the performance of the system. The system proposed through this work is evaluated on hypothetical data. This algorithm and methodology is also compatible with the continuous auditing paradigm.
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Authors

Mr. Vijay Kumar Dwivedi, Associate Professor, GLA University, Mathura (India) and currently pursuing Ph. D. from MNNIT, Allahabad. He is associated with GLA group from last 10 years. He has keen interest in investigating the triobological issue in fluid film bearing.