A METHOD FOR THE GENERATION OF MEMBERSHIP FUNCTIONS USING OPERATING STATES IN A GLASS FURNACE

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ABSTRACT
A fuzzy set is fully defined by its membership function (MF) and the design of the membership function is an integral part of the whole fuzzy system design. This work looked at using operating states in a chemical plant to identify the membership function parameters. There were three operating states discovered, namely, the not normal operating state (NNOS), the normal operating state (NOS) and the transition operating state (TOS). These states were used to design the MFs of the fuzzy variables with specific reference to setting the limits for the MF and describing the linguistic terms and shape of these terms for the MF. The work showed that dropping sharply and rising sharply could be associated with the not normal operating state and dropping gradually could be used for the normal operating states and so on.

KEY WORDS
Operating States, Membership Functions.

1. Introduction
The determination of the membership function for fuzzy variables is important for fuzzy system design. For most control applications the sets that have to be defined are easily identifiable however for other applications they have to be determined by knowledge acquisition from an expert or group of experts or some other accepted procedure. The approach adopted for acquiring the shape of any particular membership function is often dependent on the application but for fuzzy logic control problems the assumption is that the membership functions are linear - usually triangular in shape and the issues to be determined are the parameters that define the triangles. This paper looked at using the definition of three operating states in chemical plants to define the parameters of the triangles.

2. Literature Review
Many approaches are found in the literature with respect to fuzzy membership function design. Work done by Cao et al [1] looked at a clustering-analysis-based membership function formation method. The method was tested on a ball mill pulverizing system and worked well for this industrial process. Other work done by Acilar and Arslan [2] looked at using a clonal selection algorithm to optimize the fuzzy membership function for a multiple input-output system. This work focused on refining the shape of the membership function and their results show promise for the test sets that were formulated.

Fuzzy MF design has even been looked at in the design of agricultural fuzzy systems. Li et al [3] developed a method to construct fuzzy membership functions using descriptive knowledge in the absence of soil survey experts and extensive soil field observations. The method was tested in a watershed located in Heshan farm of Nenjiang County in Heilongjiang Province of China and achieved 76% accuracy.

Over the years other methods have been used to either identify or tune the parameters of the MFs for fuzzy systems. Works include those by Yang and Bose [4], Kaya et al [5], Tushir and Srivastava [6], Choi and Rhee [7] and others. The various approaches have worked well for the tested conditions in the various plants/simulations but there continues to be work in this area due to the need for accurate membership function development.

3. Data Collection and Analysis
A chemical plant was studied via review of the literature, months spent on site at the plant, log sheets available at the plants, interviews and an observational study of plant operators. The following graph shows hourly data collected from one of the plants.

Graph 1: Plot showing Raw Data for a Chemical Plant
The graph above depicts raw data collected at a chemical plant. There were some clear demarcations in the data showing periods of no swings versus periods where there are large swings of one or more variables. This suggested large changes occurring with respect to the parameters in the plant and thus implied that different operations were causing the changes. Further analysis revealed clearer clusters in the data and categorization showed three clear clusters. These clusters were linked to the operations in the plant and termed normal, not normal and transition as per industry jargon. When the data was partitioned by state there were about 85% normal operation, 5% not normal operation and 10% transition operations.

4. Definition of the States

The states were defined as follows:

- Normal Operating State (NOS)
  There were very small changes in the monitored parameters in this state.
  - Plant is maintaining setpoint within a ±1% tolerance ie the error is within 1% of the setpoint.
  - The ratio of the change of the controlled variable \(dV_c\) to the controlled variable is small or approximately 0.05 or less.

- Not Normal Operating State (NNOS)
  There are large changes to the monitored parameters in this state.
  - Error from the setpoint is outside a 1.5% band of tolerance.
  - The ratio of the change of the controlled variable \(dV_c\) to the controlled variable is large or approximately greater than 0.05.

- Transition Operating State (TOS)
  The monitored parameters are changing over in this state. Generally the plant operations were minimal during this phase even though the conditions were changing.
  - Error from the setpoint varies in the range 1% – 1.5 %.
  - The ratio of the change of the controlled variable \(dV_c\) to the controlled variable is between 0.05 and 0.075.

5. Fuzzy Variable Design

5.1 The Case
The chemical plant studied was a glass furnace. A diagram of the furnace is shown in Fig 1 below. The diagram shows the main sensors from which readings were taken which include the temperatures from the thermocouples and the flow sensors measuring the gas flows. The input variables chosen for this plant were the error from the setpoint, the rate of the changing temperature and the previous gas firing rate change and the output variable was the gas firing rate change.

5.2 Method for determining MF for fuzzy variable

Generally for fuzzy variable design there are three steps that are followed:

- Step 1: The range for each variable is specified and the terms and linguistics chosen.
- Step 2: The overlap of the adjacent terms are defined.
- Step 3: The shape of the membership function is determined.

This work used the definition of the states to design the fuzzy system variables for these chemical plants.

A fuzzy set could be defined as a set of ordered pairs in a certain numerical universe of discourse: \(A = \{(\mu^*_A(x), x) \mid x \in U\}\)
Where: \(\mu^*_A\) is the membership function of the fuzzy set \(A\), which assigns to each element \(x \in U\) the grade of membership \(\mu^*_A\) in the fuzzy set \(A\) considering that \(\mu^*_A(x) \in [0,1]\)
The membership function maps the numerical universe \(U\) of a given variable in the interval \(\mu^*_A : U \rightarrow [0,1]\)
If \(T_i\) \((x)\) is a fuzzy number and \(M_i\) \((x)\) its membership function for all \(x\) in the universe of discourse \(U\), then \(x\) is called as a linguistic variable, viz; changing temp, error from setpoint, previous gas adjustment etc... and \(I_2\) \((x)\) is the term set for \(x\) viz, rising sharply, rising gradually, holding, dropping gradually... The FL system is a mapping from \(U \subset R^n\) with the assumption that \(U = U_1 \times U_2 \times ... U_n\)
Where \(U_i \subset R\) for \(i = 1, 2, ..., n\).
And \(x\) means intersection.
Utilizing the three steps outlined above, the variable design was done.

**Step 1: The range for each variable is specified and the terms and linguistics chosen**
This included looking at the operating states data and associating the linguistics with the operating condition as is shown in Table 1. Note that the industry jargon is employed in the naming and the number of terms evolves out of the number of states for the operating conditions.

**Step 2: The overlap of the adjacent terms are defined**
Tables 2 – 5 show the data extracted that represented the extent of the operating states. This helped to determine the overlap of the MF terms.

**Step 3: The shape of the membership function is determined.**
Triangular MFs were used as a first trial.

<table>
<thead>
<tr>
<th><strong>Table 1: Matching MF terms to OS</strong></th>
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<tbody>
<tr>
<td>LINGUISTIC VARIABLE(LV) TERMS</td>
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<tr>
<td>Input LV: Changing Variable</td>
</tr>
<tr>
<td>Holding</td>
</tr>
<tr>
<td>Dropping gradually</td>
</tr>
<tr>
<td>Rising gradually</td>
</tr>
<tr>
<td>Dropping sharply</td>
</tr>
<tr>
<td>Rising Sharply</td>
</tr>
<tr>
<td>Input LV: Error from Setpoint</td>
</tr>
<tr>
<td>Holding</td>
</tr>
<tr>
<td>A little Above Setpoint</td>
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<tr>
<td>Plenty Below Setpoint</td>
</tr>
<tr>
<td>A Little below setpoint</td>
</tr>
<tr>
<td>Plenty Above Setpoint</td>
</tr>
<tr>
<td>Input LV: Previous Change</td>
</tr>
<tr>
<td>Maintain</td>
</tr>
<tr>
<td>Addlittle</td>
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<tr>
<td>Cutlittle</td>
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<tr>
<td>Addplenty</td>
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<tr>
<td>Cutplenty</td>
</tr>
<tr>
<td>Output LV: Current Change</td>
</tr>
<tr>
<td>Maintain</td>
</tr>
<tr>
<td>Addlittle</td>
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<tr>
<th><strong>Table 2: Changing Temperature variable</strong></th>
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<tr>
<td>Linguistic MF</td>
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<tr>
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<tr>
<td>Rising sharply</td>
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<th><strong>Table 3: Error from Setpoint variable</strong></th>
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<th><strong>Table 4: Previous Change variable</strong></th>
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<th><strong>Table 5: Current Change variable</strong></th>
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**6. Results**
The results show that the variable design with respect to membership function use triangles. The limits for the triangles follow from the state definitions. For example,
the cutplenty term is associated with not normal operations and is thus at the higher end of the limit. The simulation results with these MFs were good giving about 0-5% error for the normal operations and 0-10% for transition operations. The error was calculated from the difference between the fuzzy decision and the plant operator decision.

7. Discussion

With fuzzy logic the membership functions and their shapes are normally determined by the suitability of the descriptor to the range of the parameter eg. A large increase in flowrate (which may be termed ‘add plenty’) is from 5 m$^3$/hr to 10 m$^3$/hr. This work looked at taking these descriptors one step further and relating them for use to a particular operating state.

When the operator was running the plant under ‘normal’ conditions he made very small adjustments to his output. The descriptors he associated with these changes and conditions were ‘maintain’, ‘gradual’, ‘hold’, and ‘little’. These descriptors were used as the terms of the membership functions and their ranges are dictated by the plant and process. Generally the range of these terms is the first half ascending or descending of the variable/parameter range. Under not normal operations, the operator uses descriptors like ‘sharp’, ‘high’ and ‘plenty’. The range of these variables is the second half ascending or descending of the parameter range e.g. add plenty gas means an increase of 80 – 100 m$^3$/hr whereas add little is closer to 10 m$^3$/hr. Transition operations used descriptors that are very much like those of normal operations since small changes, if any, were made during these conditions.

8. Conclusion

The work shows good results with the accuracy of the result being higher for the NOS than the TOS and NNOS. It provides a premise for further exploratory work.

References


