Performance Improvement in Fault Diagnosis using Fuzzy Logic Type-2 Classifier

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Abstract: Complex systems often demand distributed decision making at several stages. An innovative Fuzzy Type-2 based decision making has been developed for fault diagnosis which ascertains the correctness of fault detection at primary stage. The erroneously unreported fault cases are detected by Type-2 Fuzzy Classifier.

Keywords: Fault Diagnosis, Benchmark Process Control System

I. INTRODUCTION

Type-2 fuzzy sets and systems generalize Type-1 fuzzy sets and systems so that more uncertainty can be handled. From the very beginning of fuzzy sets, criticism was made about the fact that the membership function of a type-1 fuzzy set has no uncertainty associated with it and seems to contradict the word fuzzy. In order to deal with uncertainty about the value of the membership function, Prof. Lotfi A. Zadeh proposed more sophisticated kinds of fuzzy sets in 1975, the first of which is called a type-2 fuzzy set [1].

A lot of research work on type-2 fuzzy sets has been carried out since the latter part of the 1990's by Prof. Jerry Mendel and his students on type-2 fuzzy sets and systems. Since then, more and more researchers around the world are writing articles about type-2 fuzzy sets and systems. It has been extensively used in the past few years in fuzzy logic control, fuzzy logic signal processing, rule-based classification, etc. [1-2]

II. TYPE-2 FUZZY LOGIC CLASSIFIER

The results of qualitative technique based on trend granulation and quantitative technique based on logistic regression suggest that the fault datasets correspond to nonlinear dynamic time series. Since, the conventional techniques based on linear models are not suitable for this type of data, hence it is proposed to use Type-2 FLS based classifier to deal with the impact of uncertainty on classification framework. The rules obtained as a result of trend granulation in previous section have been used here. Type-2 FLS offers better capabilities to handle linguistic uncertainties by modeling the uncertainties using type-2 membership functions.

The major components regarding fuzzification and rule base formulation by considering uncertainty issues have been briefly discussed here.

III. ANTECEDENT FUZZY SETS

The entire range of the attributes F and X considered here is divided into fuzzy sets for building FLS. In this framework, F and X play the role of antecedents and the state of operation is termed as consequent, as depicted in Figure 1-3.

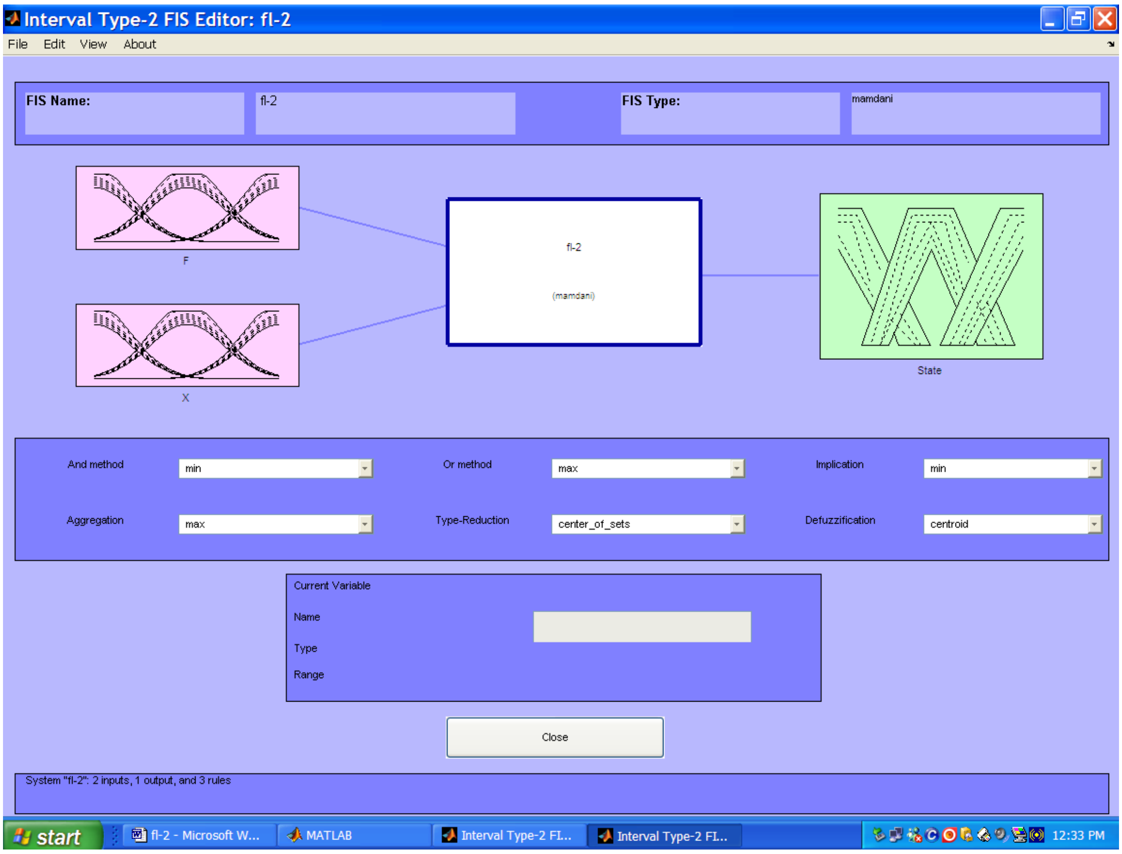

Figure 1: Inference Model

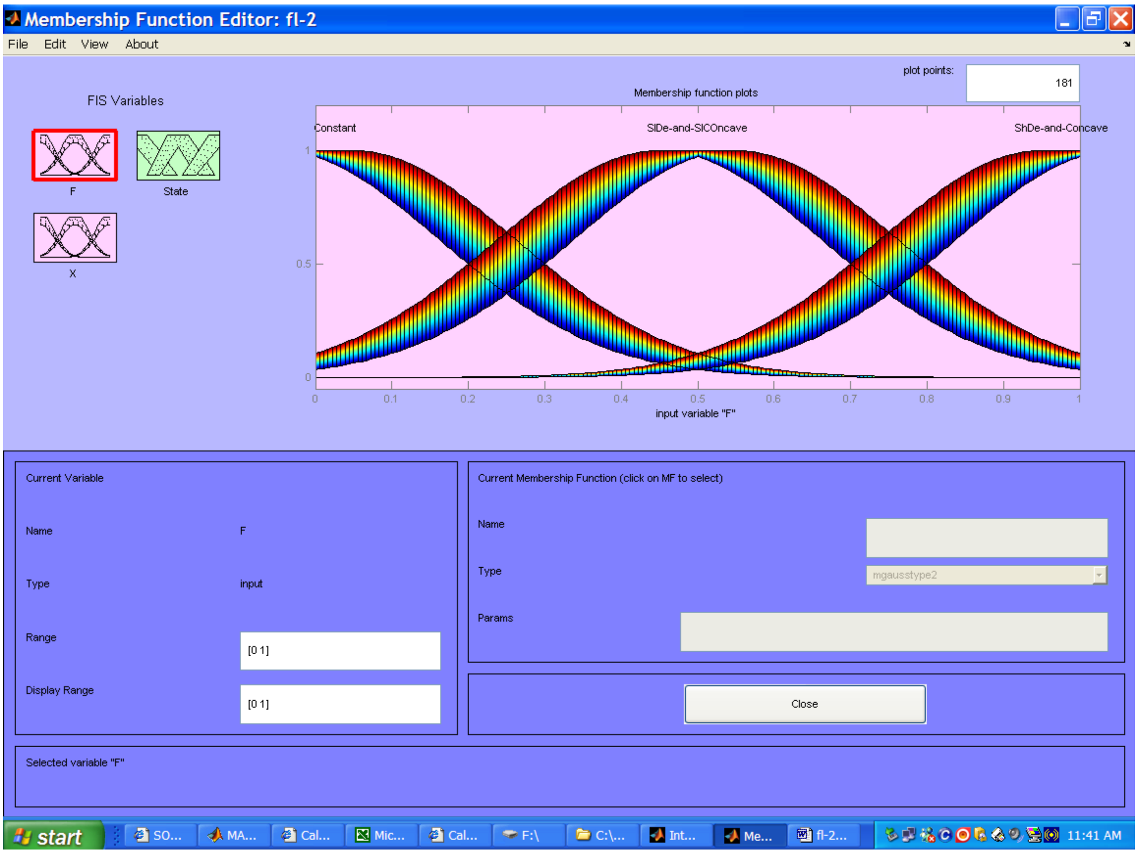

Figure 2(A): Input Membership Function for F

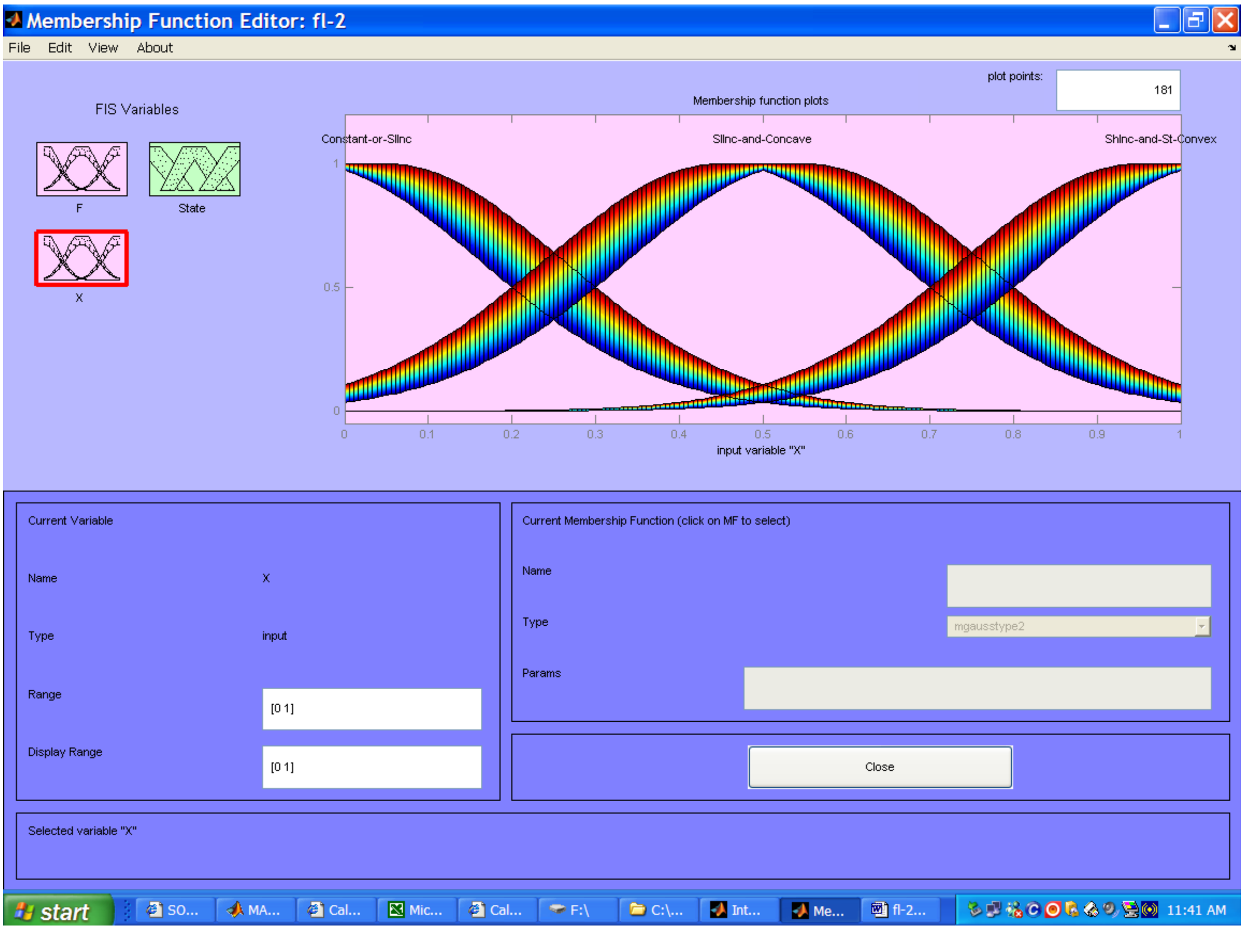

Figure 2(B): Input Membership Function for X

This fuzzy set for classification can be obtained from the experts or by the analysis of plant data sets. However, different experts may provide different assessments of a particular fuzzy set designed for a range of values for a specific attribute, based on their past experience. This causes uncertainty in the definition of antecedents of FLS. Type-2 fuzzy sets enable modeling of uncertainty due to differences in the opinion of various experts, by blurring the boundaries of the membership functions of antecedents and by defining the footprint of uncertainty (FOU).

IV. CONSEQUENT FUZZY SETS

Uncertainties in consequents arise when two or more experts relate the impact of the same antecedent fuzzy set on more than one consequent fuzzy set. In order to handle this situation three possibilities have been proposed:-

- Keep the response chosen by the largest number of experts.
- Find a weighted average of rule consequents for each rule
- Preserve the distributions of the expert responses for each rule

In this work, the second solution has been opted and the consequents are defined by all the possibilities of the combinations of fuzzy sets in the antecedents. Moreover, it is assumed that all the rules are equally probable therefore all rule consequents are equally weighted.

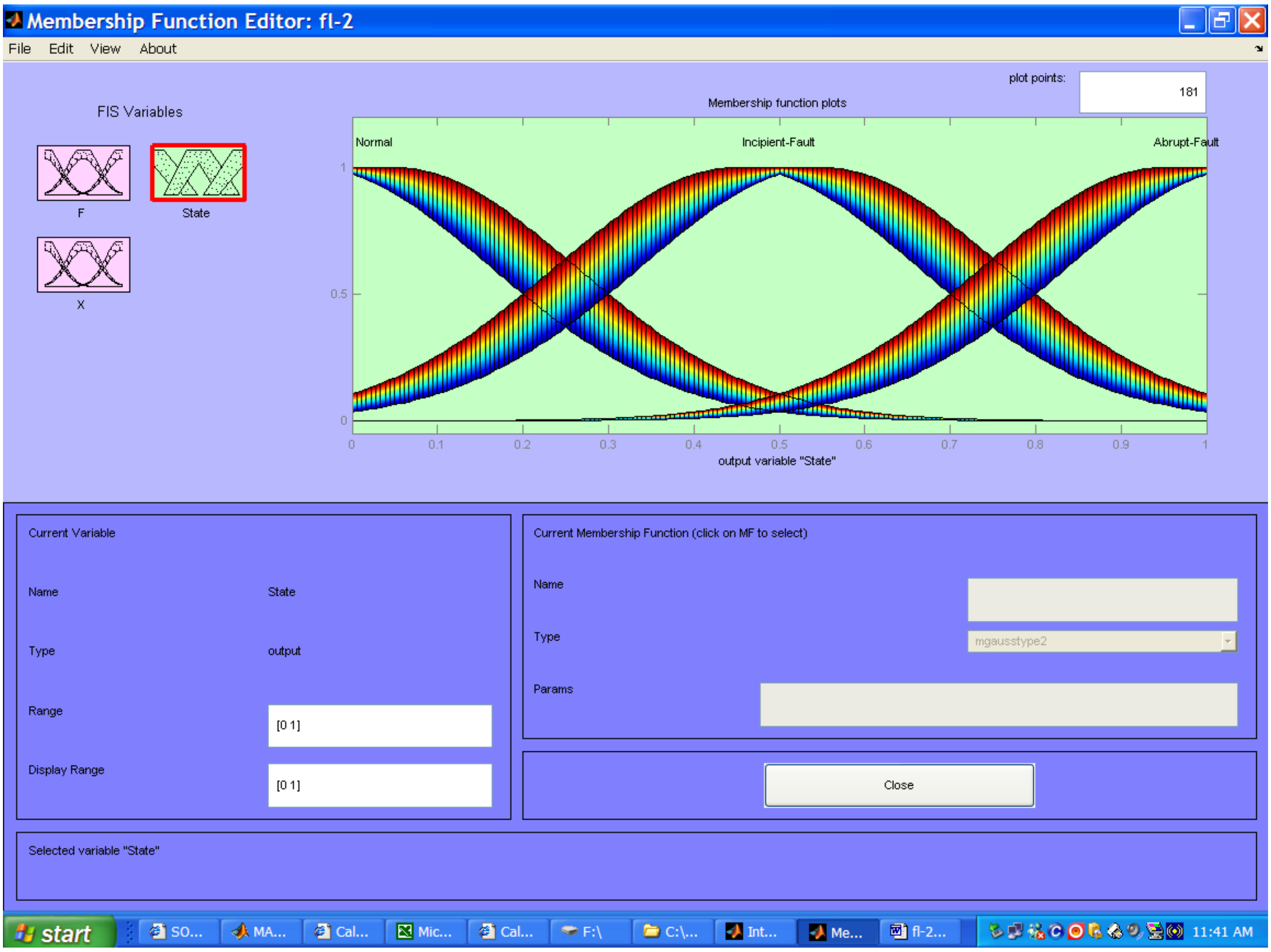

Figure 3: Output Membership Function for State of Operation

V. Training of FLS and Tuning of Membership Functions

After setting up the antecedents and the consequent fuzzy sets by incorporating the uncertainty through Type-2 representation and defining the rules using them, the next step is to train the parameters. Training of the parameters is desired to refine the rule-based linguistic relationships obtained in earlier section. The linguistic relationships are refined by using the historical records of the numerical data, which have been observed over a period of past experiences.

The distinction between Type-1 and Type-2 is associated with the nature of the membership functions, which is not essential when forming the rules. The structure of the rules remains exactly the same in the Type-1 case as shown in Figure 4, but now the sets involved are of type-2.

The rules are trained to improve their accuracy in predicting nominal effort. In this thesis, the training is carried out by propagating inputs through FLS. The tuning and modification of the parameters of various membership functions is based on computed error and steepest descent approach.

VI. Validating FLS

Finally, testing data is used to validate the performance of FLS. Since the inherent uncertainties have already been taken care of during training and the parameters are already tuned, therefore type-1 non-singleton fuzzification is used.

VII. RESULTS OF CLASSIFICATION

The rule and surface viewer have been shown in Figure 5 and Figure 6 respectively. The experimental results obtained by using Type-2 systems, as shown in table 1, have confirmed the intuition that Type-2 FLS outperforms Type-1 FLS.

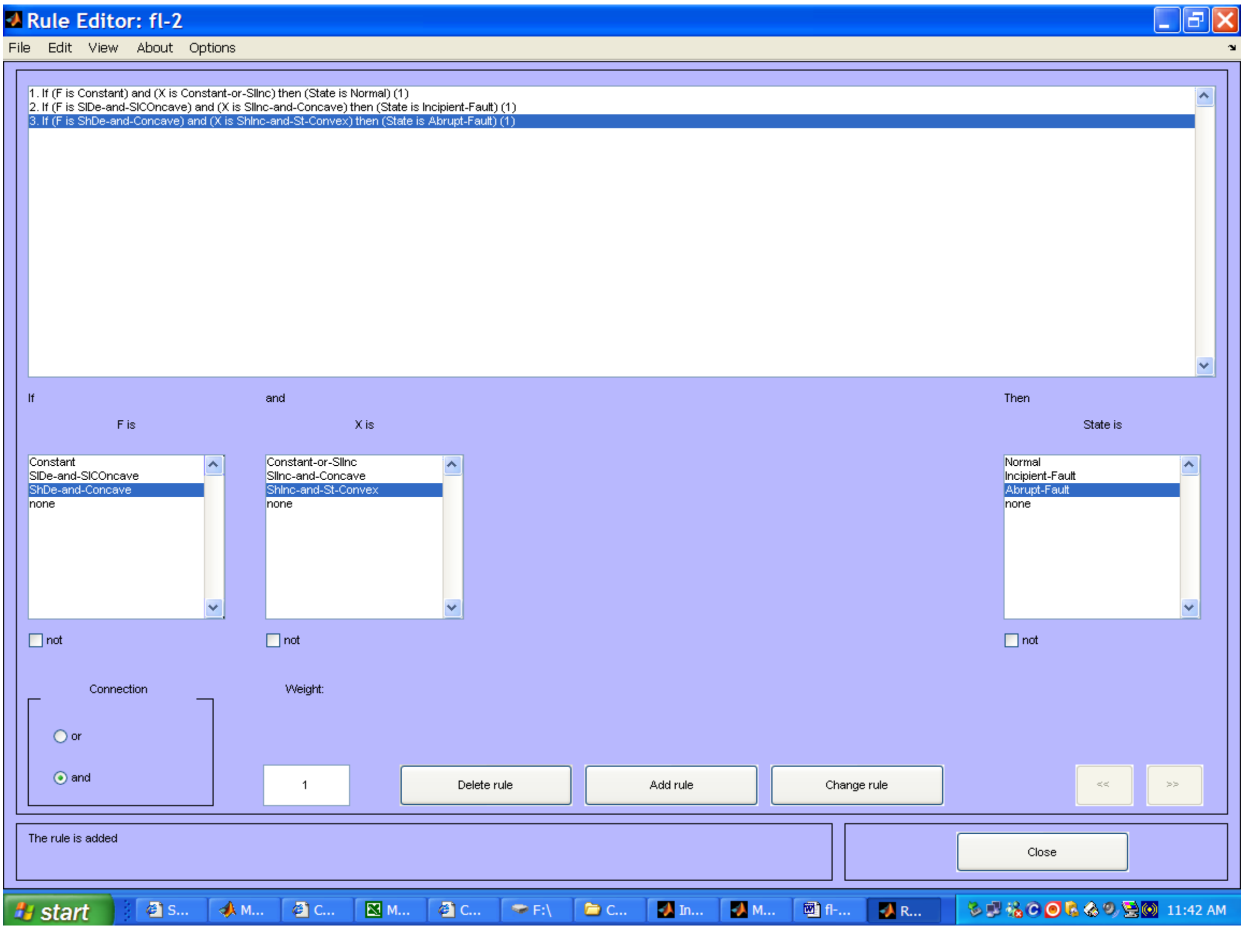

Figure 4: Perception Based Rules

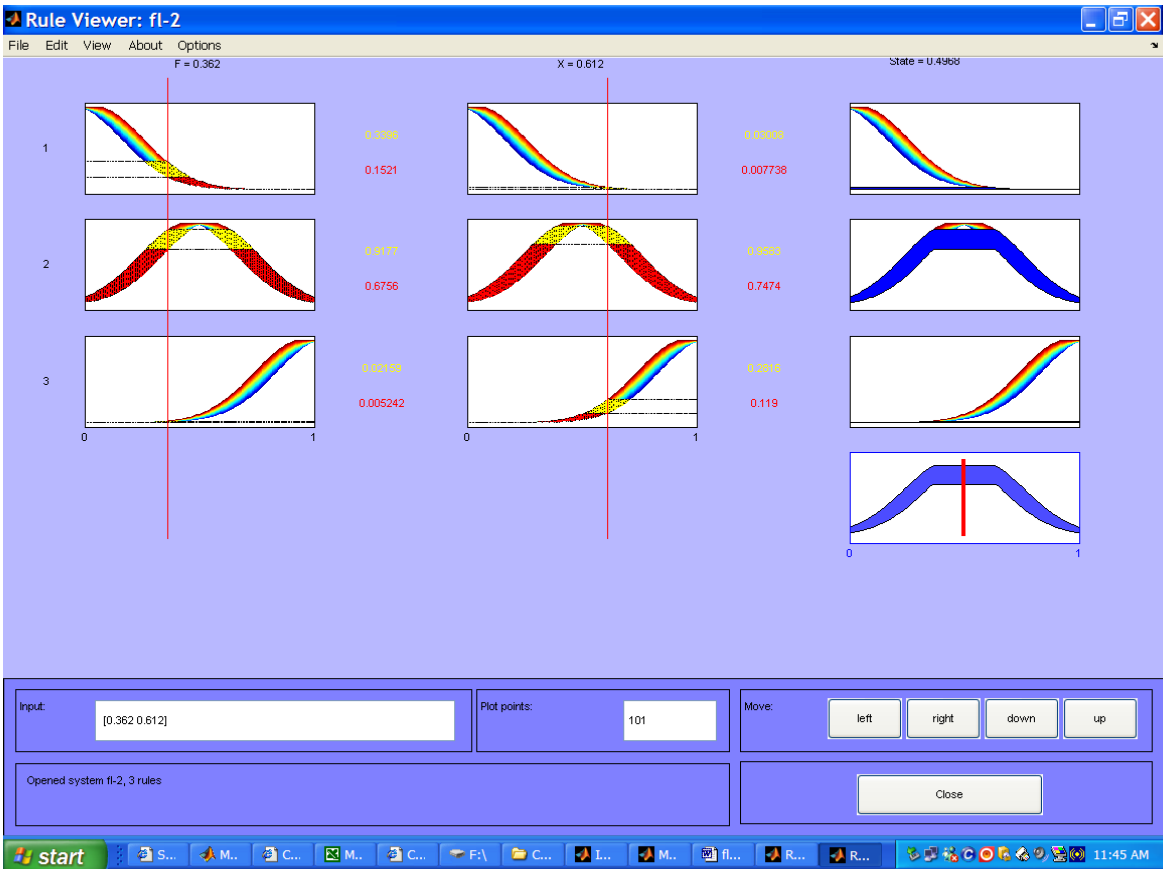

Figure 5: Rule Viewer

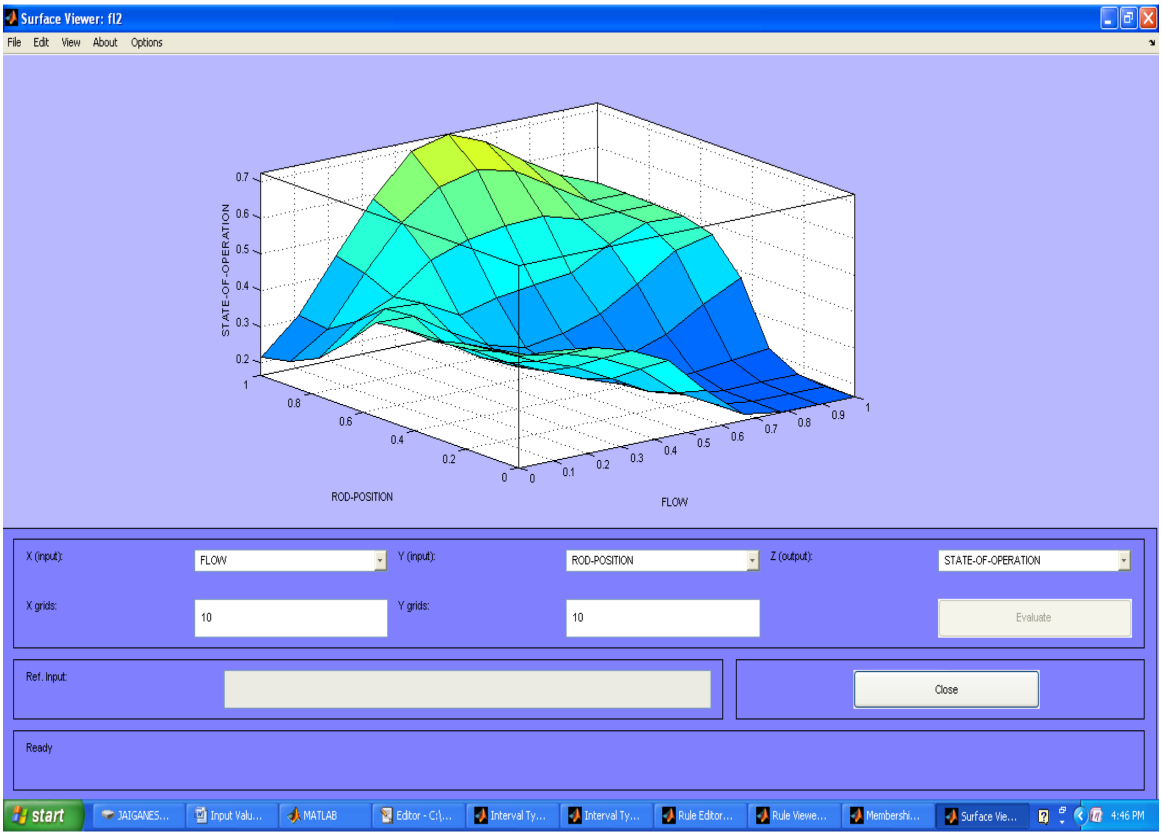

Figure 6: Surface Viewer (Inputs: F,X Output: State of Operation)

Table 1: Classification Results for Selected Dataset

Pattern No.	CV	P1	P2	T	Actual State of operation	Result of Classification
1	0.28892	0.8484	0.64977	0.2156	Normal	Normal
2	0.28092	0.83317	0.6575	0.21528	Normal	Normal
3	0.27379	0.83474	0.64597	0.21377	Normal	Normal
4	0.26756	0.84947	0.65268	0.21489	Normal	Normal
5	0.26224	0.87669	0.65749	0.21296	Normal	Normal
6	0.25785	0.89976	0.645	0.21483	Normal	Normal
7	0.25443	0.91818	0.64852	0.21672	Normal	Normal
8	0.25197	0.91585	0.65744	0.21386	Normal	Normal
9	0.25049	0.89853	0.64678	0.21941	Normal	Normal
10	0.25	0.87753	0.6448	0.21491	Normal	Normal
11	0.379562	0.87281	0.64481	0.21547	Fault	Fault
12	0.393555	0.90216	0.64942	0.21231	Fault	Fault
13	0.307372	0.9169	0.65421	0.21531	Fault	Fault
14	0.317758	0.91458	0.64431	0.21439	Fault	Fault
15	0.328863	0.89967	0.64884	0.21456	Fault	Fault
16	0.340644	0.87523	0.65756	0.21447	Fault	Fault
17	0.353054	0.84831	0.64547	0.21547	Fault	Fault
18	0.366043	0.83345	0.64743	0.21646	Fault	Fault
19	0.28892	0.916329	0.656889	0.36014	Fault	Fault
20	0.28092	0.916834	0.646129	0.374978	**Fault**	**Normal**

VIII. CONCLUSION

The performance of the system has been improved, as now there is only 1 data item in the test data set of 20 records which has been misclassified by the system.

The interval output from type-2 FLS gives more freedom to describe higher level uncertainties in human languages, but at the same time it is time consuming approach. As high performance computing is needed to process a large amount of data in time effective manner, a hybrid method is proposed in the next section for such handling cases.

VII. REFERENCES

[1] Karnik N. N. and Mendel J. M., "Introduction to Type-2 Fuzzy Logic Systems," presented at IEEE FUZZ Conf., Anchorage, AK, May 1998.

[2] Karnik N. N., Mendel J. M., Fellow, "Type-2 Fuzzy Logic Systems", IEEE, and Qilian Liang, IEEE Transactions on Fuzzy Systems, VOL. 7, NO. 6, DECEMBER 1999, pp 643-658.

