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SELECTION OF ALTERNATIVE UPDATING POLICY UNDER COGNITIVE THEORY FRAMEWORK

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ABSTARCT:
The decision making strategy adopted by the fault diagnosis system should consider the benefit of acquiring information versus introducing measurement error into system knowledge. Further, it is expected to revise its beliefs by judging the truth of informationally valuable hypotheses. It should avoid rejecting important hypotheses simply on the basis of the probability of truth and error and should be indifferent to the truth or error of a hypothesis it regards as informationally unimportant. In this paper, decision making for fault diagnosis for the DAMADICS problem has been considered under the framework of cognitive decision theory.

Keywords: **Fault Diagnosis, Benchmark Process Control System**

I. INTRODUCTION

There are a large number of process variables available for measurement in the sugar plant taken up for this research. Hence, for efficient fault diagnosis, the selection of more informative sensors and continuous monitoring of their health condition is an important problem that needs epistemological consideration. Sensor uncertainty depends on what is observed rather than the sensor itself. Also, inability of the sensor to measure all relevant attributes or ambiguous observations can all contribute to uncertainty. The advantage of multiple sensors is that the observations of each one may be combined into an improved estimate of the state compared to one derived from a single sensor. Hence, each sensor may play the role of a potential contributor to a composite decision making process. In this paper, decision making for fault diagnosis for the DAMADICS problem[1] has been considered under the framework of cognitive decision theory[2-3].
Epistemological considerations have been made in this paper which may further help in improvement of the results by making the decision making system self learning and intelligent

II. PROPOSED METHODLOGY

On the basis of decisions obtained at primary and secondary level stage in relation to normal, abrupt and incipient fault conditions by the computational decision making system, a priori probabilities are assigned to the computational decision making system, as shown in Figure 1. The system adopts a particular probability distribution as credence function. Here, the epistemological decisions under evaluation are decisions of adopting a particular credence function.

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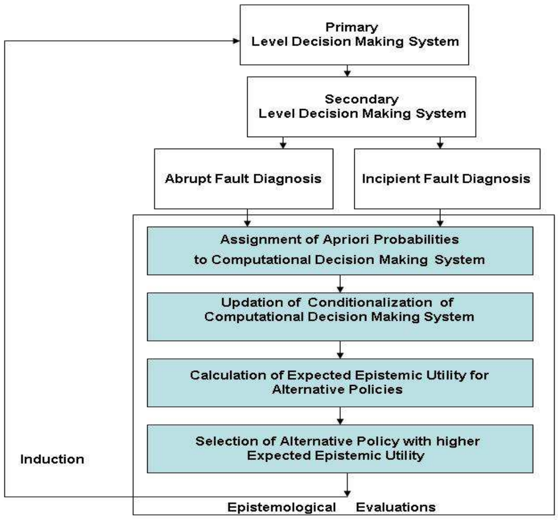

Figure 1: Proposed Framework for Epistemological Evaluations

Since such decisions are prescriptions for how to revise system's beliefs in the light of new evidence, they are also termed as updating policies. Updation of conditionalization of the computational decision making system leads to the possible posterior probability distributions.

In the pursuit of acquiring error-free knowledge, epistemic utility of taking a decision in a given scenario is evaluated and analyzed under the framework of Cognitive Decision theory. Expected Utility Function helps in evaluating the degree of fit between the truth and the belief states of the computational decision making system. Hence, in any given epistemic predicament, that alternative policy (i.e., epistemologically rational action) is selected which maximizes the value of this function.

III. IMPLEMENTATION OF PROPOSED METHODLOGY

In the primary decision making stage the granulation of measured parameters was done on the basis of max-min ranges. Instead of this, the criteria of granulation are now chosen so that all the granules have a **spread of ± 3 times of standard deviation around the mean value of the dataset** for the selected class. Thus, an alternative preliminary Decision Making policy is now available. This selection of policy is based on the study of the distribution of the data of two states of the system, namely normal and fault conditions.

For illustration, distribution of CV, P1, X, F corresponding to fault F8 i.e., Twisted servo-motor's piston rod fault is shown in Figure 2. It can be observed that all these parameters generally follow the Gaussian Normal Distribution; hence the above selection of alternative policy appears to be justified.

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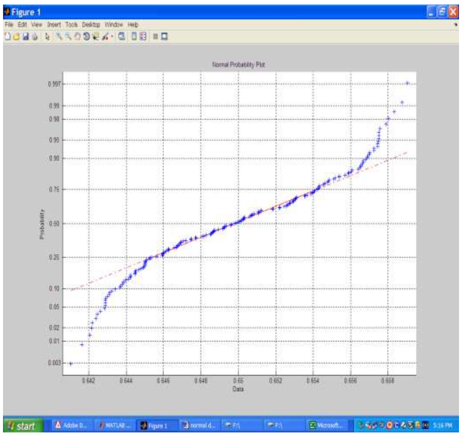
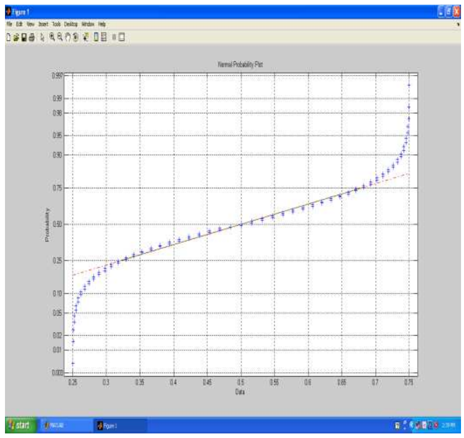
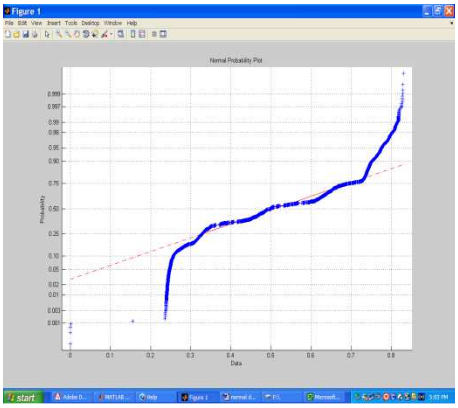

CV


P1


X

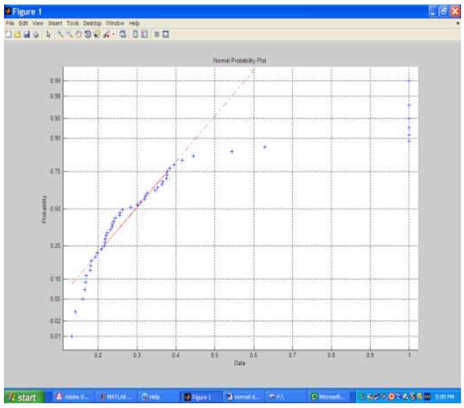

F

Figure 2: Distribution of Measured Parameters Values

For the Data set considered for Class 0 (Normal Condition) and Class 1 (Fault Condition) following results are obtained on the basis of alternative policy as indicated in Table 1-2.

Table 1: Values (p.u.) of Measured Parameters (Class 0 – Normal Condition)

	Mean (m)	**Standard deviation (sd)**	**m+3 sd**	**m-3 sd**
CV	0.263817	0.875232	0.650595	0.215223
P1	0.076837	0.030722353	0.005022	0.001713791
P2	0.494328	0.967399058	0.665662	0.220364374
T	0.033306	0.783064942	0.635528	0.210081626

Table 2: Values (p.u.) of Measured Parameters (Class 1 – Fault Condition)

	Mean (m)	**Standard deviation (sd)**	**m+3 sd**	**m-3 sd**
CV	0.555921	0.8896273	0.649507	0.2453558
P1	0.089686	0.029035598	0.004722	0.061200152
P2	0.82498	0.976734093	0.663674	0.428956257
T	0.286861	0.802520507	0.63534	0.061755343

Accordingly, the ranges of actual values of measured parameters have been shown in Table 3.

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Table 3: Ranges of the Measured Parameters within the classes

Measured Parameter	Class 0		Class 1	
CV	3.33	49.43	28.68	82.49
P_1	783.06	967.39	802.52	976.73
P_2	635.52	665.66	635.33	663.67
T	31.51	33.05	9.26	64.34

The ranges of the values presented in Table have been granulated, depending on the classes (class 0 – Normal Condition, class 1 – Fault Condition), as illustrated in Table 4.

Table 4: Granulated ranges of the Measured Parameters

Measured Parameter	Range		Granules	Class 0	Class 1
CV	3.33	28.68	A11	Class 0	
	28.69	49.43	A12	Class 0	Class1
	49.44	82.498	A13		Class1
P1	783.06	802.51	A21	Class 0	
	802.52	967.39	A22	Class 0	Class1
	967.40	976.73	A23		Class1
P2	635.33	635.51	A31		Class 1
	635.52	663.67	A32	Class 0	Class 1
	663.68	665.66	A33	Class 0	
T	9.2	31.4	A41		Class1
	31.5	33.05	A42	Class 0	Class1
	33.06	64.34	A43	Class 0	

The following Perception-Based Rules are now obtained:-

R^1: IF CV is A_{11} or CV is A_{12} and P1 is A_{21} or P1 is A_{22} and P2 is A_{32} or P2 is A_{33} and T is A_{42} or T is A_{43} THEN Class 0.

R^2: IF CV is A_{12} or CV is A_{13} and P1 is A_{22} or P1 is A_{23} and P2 is A_{31} or P2 is A_{32} and T is A_{41} or T is A_{42} THEN Class 1.

The classification system includes the above mentioned rules and membership functions are expressed accordingly. Finally, the results of classification based on alternative policy are obtained from these rules and have been depicted as in Table 5.

Table 5: Results for Selected Datasets

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

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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	0.64695	0.87281	0.64481	0.21547	Fault	Fault
12	0.63396	0.90216	0.64942	0.21231	Fault	Fault
13	0.62044	0.9169	0.65421	0.21531	Fault	Fault
14	0.60644	0.91458	0.64431	0.21439	Fault	Fault
15	0.59203	0.89967	0.64884	0.21456	Fault	Fault
16	0.57725	0.87523	0.65756	0.21447	Fault	Fault
17	0.56217	0.84831	0.64547	0.21547	Fault	Fault
18	0.54685	0.83345	0.64743	0.21646	Fault	Fault
19	0.379562	0.916329	0.656889	0.36014	Fault	Fault
20	0.393555	0.916834	0.646129	0.374978	Fault	Normal

On the basis of revised results from primary & secondary decision making systems, now the probabilities are assigned.

IV. RESULTS

As mentioned earlier, by considering the historical data base of the plant and experts' opinion, the a priori probability of occurrence of fault is about 20 % and reliability of primary decision making system/ sensor is 95%.

Thus, the following probabilities may be assigned at Primary Level Decision Making System:

$$q(N) = 0.8 * 0.95 = 0.76$$
$$q(F) = 0.2 * 0.95 = 0.19$$

Also the following probabilities may be assigned for the falsely assumed states of operation, taking into account the fact that 5% of misclassified cases arising due to unreliability of decision making system/ sensor are distributed evenly:

$$q(N') = 0.8 * 0.05 = 0.04$$
$$q(F') = 0.2 * 0.05 = 0.01$$

At Secondary Level Decision Making System for confirmation of Normal Condition, from the earlier results obtained, one case was wrongly classified as faulty out of data set of twenty with misclassification error as 5%. Hence, the probabilities of output at this stage may be assigned as:

$$q(N\,N) = 0.722$$
$$q(NF) = 0.038$$

With fourteen abrupt fault cases possible out of spectrum of nineteen faults considered, the probability of normal being classified as abrupt fault condition and the probability of normal being classified as incipient fault condition can be calculated respectively as :-

$$q(NFA) = 0.038 * 14/19 = 0.028$$
$$q(NFI) = 0.038 * 5/19 = 0.01$$

Similarly, at Secondary Level Decision Making System for confirmation of Fault Condition, from the results obtained with misclassification error for abrupt fault as about 1% and for incipient faults about 15%; the following probabilities of output at this stage may be assigned :-

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q(FA)	=	0.14
q(FI)	=	0.05
q(FAA)	=	0.1386
q(FAN)	=	0.0007
q(FAI)	=	0.0007
q(FII)	=	0.0425
q(FIN)	=	0.00375
q(FIA)	=	0.00375
q(N'A)	=	0.0295
q(N'AA)	=	0.029
q(N'AN)	=	0.0015
q(N'AI)	=	0.0015
q(N'I)	=	0.0105
q(N'II)	=	0. 009
q(N'IN)	=	0.00075
q(N'IA)	=	0.00075
q(F'N)	=	0.0095
q(F'F)	=	0.0005
q(F'FA)	=	0.000495
q(F'FI)	=	0.000005

This Probability assignment has been depicted in Figure 3.

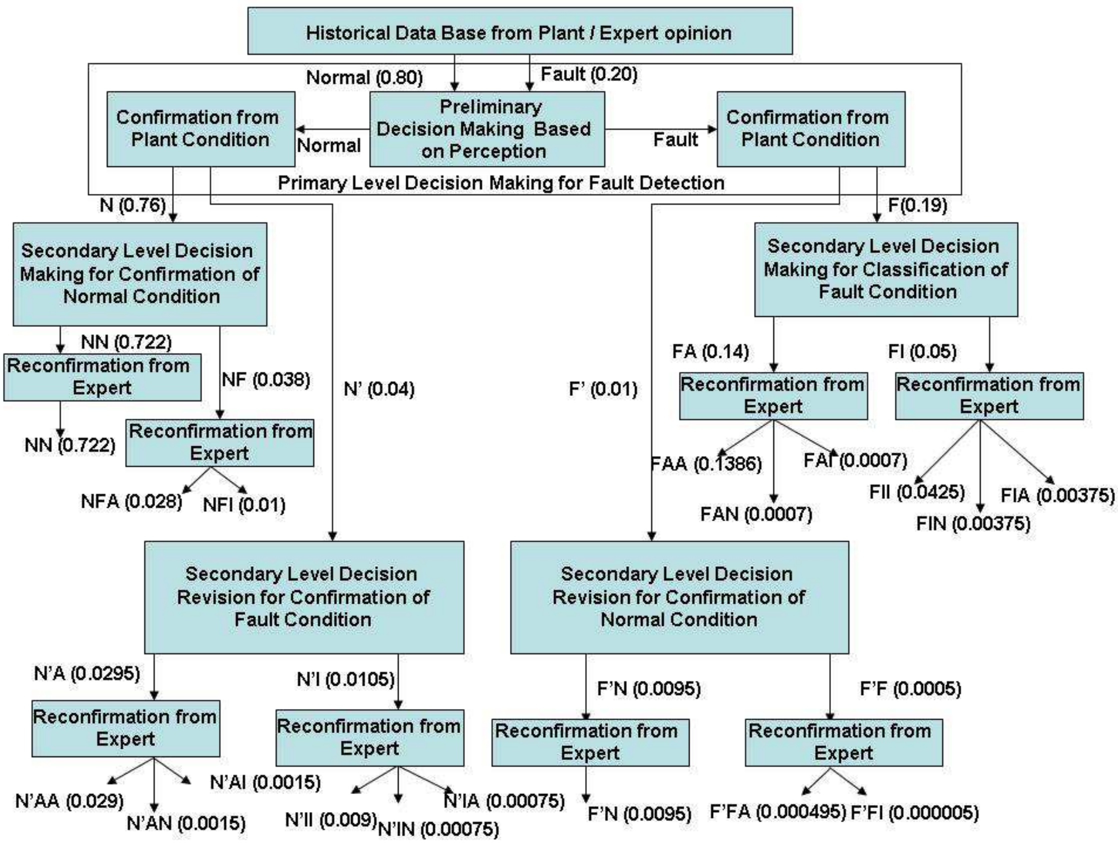

Figure 3: Assignment of A priori Probabilities for Alternative Policy

V. DISCUSSION

The proposed methodology provides scope for fine tuning of the decision making system for the continuous improvement of results, thereby making the decision making system Self Learning and Intelligent. The above analysis is utilized for improving the fault diagnosis results by consideration of possible alternatives in the Perception Based Decision Making System.

REFERENCES

[1] Witczak M., Korbicz J., Mrugalski M., Patton R. J., "A GMDH Neural Network-Based Approach to Robust Fault Diagnosis: Application to the DAMADICS Benchmark Problem", March 04.
[2] Greaves H. and Wallace D., "Justifying conditionalization: Conditionalization maximizes expected epistemic utility", February 26, 2005.
[3] Stirling W. C. and Morrell D. R., "Convex Bayes Decision Theory" IEEE Transactions on Systems, Man, and Cybernetics, January/ February 1991, Vol. 21, No. I.