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# Self Learning and Intelligent Fault Diagnosis System based on Assessment of Epistemic Utility

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ABSTRACT

*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.*

Keywords : DAMADICS Benchmark Process Control System, Fault Diagnosis, Epistemic Utility

**Introduction**

A complete fault diagnosis system requires not only the identification of the various types of abrupt and incipient faults, but also robustness against signal blackout due to communication channel failure and sensor malfunctioning. Hence, the design of decision making system should now focus towards handling of the eventuality of sensor failure in the proposed framework of epistemological decision making for fault diagnosis for the DAMADICS problem. [1-2]

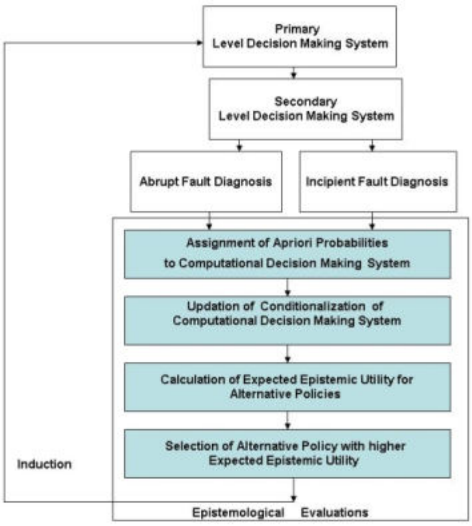
In this paper, decision making for fault diagnosis for the DAMADICS problem has been considered under the framework of cognitive decision theory [3-4]. The guiding principle for this purpose is the premise that a rational epistemic computational system always prefers the decision that maximizes the expected epistemic utility.

**Proposed Methodology**

This work proposes Epistemological Evaluation for arriving at rational decision using a generalized Cognitive Decision Theory Framework. The objective here is to ascertain that the misclassifications in the results obtained in Primary or Secondary Decision Making System for abrupt and incipient fault diagnosis were at least not due to the noise, sensor failure etc.

The computational decision making system contemplates a set of mutually exclusive and jointly exhaustive possible states on the basis of all possible outcomes. On the basis of decisions obtained at primary and secondary level stage in relation to normal, abrupt and incipient fault conditions, 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.

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 decision) is selected which maximizes the value of this function.

### Application of Proposed Methodology

The proposed methodology is now applied on the DAMADICS problem data set to demonstrate its efficacy. Decision making steps under cognitive theory framework are discussed in following sub-section.

In this section, following notations have been used for sake of brevity:-

N: Normal

F: Fault

A: Abrupt Fault

I: Incipient Fault

Experts' opinion on the basis of the historical data base of the plant suggests that the a priori probability of occurrence of fault in a sugar plant is about 20 % and the projected reliability of primary decision making system including sensors is 90%.

This rationale is used for assigning 90% (0.90) reliability of the proposed decision making system. Thus, the following probabilities may be assigned at Primary Level Decision Making System corresponding to normal and fault condition respectively:-

$$p(N) = 0.8*0.9 = 0.72$$
$$p(F) = 0.2*0.9 = 0.18$$

Also, the following probabilities may be assigned for misclassified state of operation taking into account the fact that there are 10% misclassified cases among both the categories, due to unreliability of primary decision making system/ sensor:-

$$p(N') = 0.8*0.1 = 0.08$$
$$p(F') = 0.2*0.1 = 0.02$$

At Secondary Level Decision Making System for confirmation of normal condition, from the 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:-

$$p(NN) = 0.684$$
$$p(NF) = 0.036$$

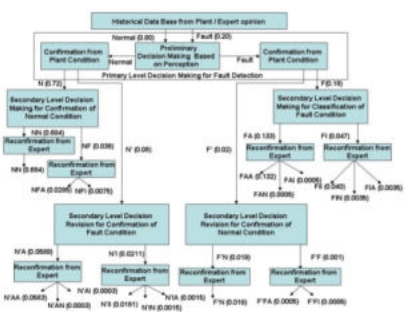
There are fourteen types of abrupt fault cases out of the possible nineteen types of faults considered. Hence, the probability of the normal condition being classified as an abrupt fault condition and the probability of it being classified as incipient fault condition can be calculated respectively as

$$p(NFA) = 0.036*14/19 = 0.0285$$
$$p(NFI) = 0.036*5/19 = 0.0075$$

Similarly, for confirmation of Fault Condition at Secondary Level Decision Making System, the results obtained have an associated misclassification error of about 1% for abrupt fault as about 15% and for incipient faults.

This assignment has been depicted in Figure 2.

Figure 2: Assignment of apriori Probabilities




After observing the results of fault diagnosis, the Computational System reassesses the degrees of belief as to whether or not the fault diagnosis system is functioning properly. It decides the process of reassessment in advance and the selection of credence distribution in the event of observing normal condition or fault condition (abrupt or incipient).

The possible states for the considered problem, may be contemplated by the Computational System as follows:

$S = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8, s_9, s_{10}, s_{11}, s_{12}, s_{13}, s_{14}, s_{15}, s_{16}, s_{17}, s_{18}\}$

Where:-

$s_1$ = State of Operation detected by Primary Decision Making System is Normal, outcome of fault diagnosis from Secondary Decision Making System is Normal and final outcome after reconfirmation from expert is Normal.

$s_2$ = State of Operation detected by Primary Decision Making System is Normal, outcome of fault diagnosis from Secondary Decision Making System is Fault and final outcome after reconfirmation from expert is Abrupt Fault.

and so on.

Computational system's prior state is represented by the following probability distribution over S by assigning a priori probability to each case:

$$p*(s1) = 0.684$$
$$p*(s2) = 0.0285$$

and so on.

The experimental data structure for the Computational Decision Making system for the DAMADICS problem is given by:-

$E = \{N, A, I\}$

where:- $N = \{s_1, s_5, s_8, s_{10}, s_{14}, s_{17}\}$, $A = \{s_2, s_4, s_9, s_{11}, s_{13}, s_{18}\}$, $I = \{s_3, s_6, s_7, s_{12}, s_{15}, s_{16}\}$.

Computational system requires cognitive decision regarding whether to update by conditionalization from prior p* obtained from the result of the fault diagnosis, or by a particular rival updating alternative policy (AP) as given below.

Updating by conditionalization from the prior p would lead to the following possible posteriors:-

Cond P (N) = p(·/N) =: pN, where

$$p_N(s_1) = 0.914072$$
$$p_N(s_2) = 0$$

and so on.

Where $p_N(s_1)$ is probability of occurrence of state $s_1$, when primary decision making has detected the State of Operation as Normal.

Similarly,

Cond P (A) = p (·/A) =: $p_A$, where

$$p_A(s_1) = 0$$
$$p_A(s_2) = 0.155823$$

Cond P (I) = p(·/I) =: $p_I$, where

$$pI(s1) = 0$$
$$pI(s2) = 0$$

Assignment of apriori Probabilities to Computational System for Alternative Policy

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:

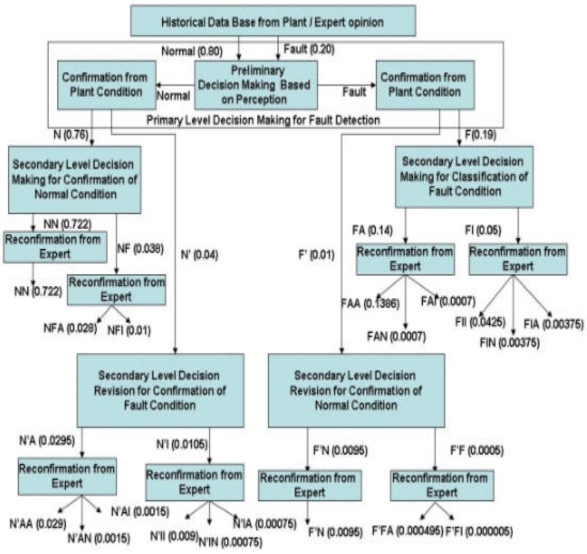
| | | | | |
|---|---|---|---|---|
| q(N') | = | 0.8 *0.05 | = | 0.04 |
| q(F') | = | 0.2*0.05 | = | 0.01 |

In similar fashion,

| | | | | |
|---|---|---|---|---|
| q(N N) | = | 0.722 | | |
| q(NF) | = | 0.038 | | |
| q(NFA) | = | 0.038*14/19 | = | 0.028 |
| q(NFI) | = | 0.038*5/19 | = | 0.01 |

This Probability assignment has been depicted in Figure 3.

Figure 3: Assignment of apriori Probabilities for Alternative Policy




**Epistemic Utility Function**

The Computational system holds a particular epistemic utility function, U , assigning a real number to each pair consisting of a state and a probability distribution. U(s, p) represents the epistemic value ("epistemic utility") of holding credence function p when state s in fact obtains.

For arbitrary state s Є S and probability distribution p over S, Epistemic utility is given by equation (1):-

$EU^p(a) = \Sigma_{Ej \in E\ s \in Ej}\ p(s) \cdot U(s, a(E_j))$ (1)

The expected epistemic utility of updating by conditionalization from prior p*, given experiment E, is given by equation 1.

$Eu^p *(\text{Cond P}) = p^*(s_1) \cdot U(s_1, p_N) + p^*(s_2) \cdot U(s_2, p_A) + p^*(s_3) \cdot U(s_3, p_I) + p^*(s_4) \cdot U(s_4, p_A) + p^*(s_5) \cdot U(s_5, p_N) + p^*(s_6) \cdot U(s_6, p_I) + p^*(s_7) \cdot U(s_7, p_I) + p^*(s_8) \cdot U(s_8, p_N) + p^*(s_9) \cdot U(s_9, p_A) + p^*(s_{10}) \cdot U(s_{10}, p_N) + p^*(s_{11}) \cdot U(s_{11}, p_A) + p^*(s_{12}) \cdot U(s_{12}, p_I) + p^*(s_{13}) \cdot U(s_{13}, p_A) + p^*(s_{14}) \cdot U(s_{14}, p_N) + p^*(s_{15}) \cdot U(s_{15}, p_I) + p^*(s_{16}) \cdot U(s_{16}, p_I) + p^*(s_{17}) \cdot U(s_{17}, p_N) + p^*(s_{18}) \cdot U(s_{18}, p_A)$

**$EU^p$*(Cond P) = -0.44763**

$EU^q *(\text{Cond AP}) = q^*(s_1) \cdot U(s_1, q_N) + q^*(s_2) \cdot U(s_2, q_A) + q^*(s3) \cdot U(s_3, q_I) + q^*(s_4) \cdot U(s_4, q_A) + q^*(s_5) \cdot U(s_5, q_N) + q^*(s_6) \cdot U(s_6, q_I) + q^*(s_7) \cdot U(s_7, q_I) + q^*(s_8) \cdot U(s_8, q_N) + q^*(s_9) \cdot U(s_9, q_A) + q^*(s_{10}) \cdot U(s_{10}, q_N) + q^*(s_{11}) \cdot U(s_{11}, q_A) + q^*(s_{12}) \cdot U(s_{12}, q_I) + q^*(s_{13}) \cdot U(s_{13}, q_A) + q^*(s_{14}) \cdot U(s_{14}, q_N) + q^*(s_{15}) \cdot U(s_{15}, q_I) + q^*(s_{16}) \cdot U(s_{16}, q_I) + q^*(s_{17}) \cdot U(s_{17}, q_N) + q^*(s_{18}) \cdot U(s_{18}, q_A)$

**$EU^q$*(Cond AP) = -0.31823**

Since $Eu^q$*(Cond AP) > $Eu^p$*(Cond P), the system will choose to update by the alternative policy AP rather than by existing policy P. It has been further verified that the proposed methodology AP yields better results and also the recognition rates of diagnosis system improve with time.

**Inference**

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.

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