Possible Extension of Research in Fault Diagnosis and Intelligent Control of Complex Systems

Dr. Tarun Chopra

Abstract: In this paper, at first general conclusions of research work carried out by the author in the area of Fault Diagnosis Intelligent Control of complex systems have been presented. Then in next section the possible extensions of future research have been discussed.

Keywords: Fault Diagnosis, Benchmark Process Control System

I. INTRODUCTION

The research work by author has brought into limelight the following general conclusions:-

Fault Diagnosis in complex systems often involves faults of highly overlapping nature. This poses a challenging decision making problem due to limited availability of data and critical importance of the fault diagnosis task due to high cost factor and possible harm to human life in case of small damages developing into catastrophes. Keeping in view the time criticality of the problem, the task of decision making has been divided into two distinct stages. At the initial level, perception based approach has been proposed and found to be highly effective for quickly arriving at decisions thereby saving precious time, in the case of exigencies. The perception based rules in primary decision making aim at separating normal condition from fault condition cases. Thereafter, further confirmation of the correctness of initial diagnosis is carried out at secondary stage with the help of Type-2 Fuzzy classifier. The membership functions of this classifier are tuned by using epistemic rules generated by trend granulation. This scheme of action has yielded promising results. Further, a hybrid classifier based on Type-2 Fuzzy C-Means Clustering has been proposed and has succeeded in clearly separating out the normal, abrupt and incipient fault cases.

Computational decision making models based on epistemological considerations have been proposed for further separation of abrupt and incipient fault classes and have shown substantial improvement over existing techniques.

The problem considered in this work has a high level of complexity, thus limiting the success of individual approaches of fault diagnosis. It has hence become necessary to apply a variety of decision making techniques which have their own individual strengths and weaknesses and finally integrate their results to arrive at the best possible decision.

Dr. Tarun Chopra is working as Associate Professor, Department of Electrical Engineering, Govt. Engineering College Bikaner, India-334004, Email: tarun_ecb@rediffmail.com

An epistemological integration framework has been proposed for this purpose. Thus, GMDH based abductive network[1] has been employed for committee based decision making thereby integrating the outputs of eleven techniques (from three major genres i.e. statistical, machine learning and neural network based techniques) for abrupt fault classes.

The separation of the nearly inseparable incipient fault classes has been carried out by using an innovative approach based on Self-Organizing Maps [2]. This can be visualized as an epistemological approach based on constructive learning [3], which involves qualitative restructuring and modification of internal knowledge representations.

Finally, epistemic utility of the possible policies has been evaluated on the basis of the results from earlier stages of fault diagnosis. This provides scope for fine tuning of the decision making system for the continuous improvement in results.

The proposed approach has yielded far better results as compared to those obtained by other researchers on DAMADICS benchmark problem[4].

II. POSSIBLE EXTENSION OF RESEARCH WORK

Some preliminary work has been carried out to find the important sensors for diagnosis of individual faults, as shown in table 1. The value indicated in parenthesis along with the measured parameter represents the correct percentage of classification obtained when the data of only individual sensor is used for the purpose of classification. It is pertinent to mention here that the set of nineteen faults considered in DAMADICS benchmark also includes three sensor faults, namely F13 (Rod displacement sensor fault), F14 (Pressure sensor fault) and F19 (Flow rate sensor fault).

Table 1: Analysis of Importance of Sensors

S.No.	Fault	Sensors Useful for fault detection (Correct Classification %)
1	F1	P1(85.8%),T(86.3%)
2	F2	P2(87.3%),T(88.8%),F(89.1%)
3	F3	CV(87.8%), P1(87.7%),P2(91.2%),X(90%),T(86.2%)
4	F4	CV(81.8%), P1(90%)
5	F5	P2(84.8%),X(84.3%)
6	F6	CV(87.6%), X(84.7%)
7	F7	X(89.1%),F(86.9%),T(100%)
8	F8	CV(83.8%), X(83.6%)
9	F9	CV(91.9%), X(94%),F(95.7%)

10	F10	F(85.3%), X(83.9%)
11	F11	X(81.8%),F(86.2%)
12	F12	P2(85.1%),F(81.3%)
13	F13	F(82.1%)
14	F14	P2(85.3%),T(81.3%)
15	F15	X(96.3%),T(94.9%)
16	F 16	P2(94.2%),X(95.9%),T(93%)
17	F17	CV(87.3%), P2(81.3%),X(86.7%),T(90%)
18	F 18	CV(88.6%), P1(82.6%), P2(89.1%),X(86.7%),T(87.8%)
19	F 19	P1(87.2%), P2(87.5%),T(86.2%)

This analysis can be used if the perception based decision making has already indicated the possible occurrence of particular faults. Thus, if the fault is either F2 or F12, the correct diagnosis can be made by just monitoring the level of sensor T, which yields 88.8% correct classification for F2, whereas there is no significant difference in the classification rates of other two sensors (P2, F for F2 and P2, F for F12 with correct classification rates of 87.3%,89.1%,85.1% and 81.3% respectively).

Further study was carried out for the selection of minimum possible sensors for modeling of flow for abrupt and incipient classes of faults. For this purpose, all the possible combinations of sensors (one set of five sensors, five possible sets involving four sensors each and ten possible sets of three sensors each) have been considered for modeling of flow as output. RMSE and MAE have been calculated for each case. The results have been summarized in table 2.

Table 2: Results for Selection of Sensors for modeling Flow in Abrupt and Incipient Fault Conditions

		RMSE	MAE
CV,P_1, P_2,T,X			
All	Training	0.096	0.059
	Testing	0.102	0.066
Abrupt	Training	0.094	0.057
	Testing	0.099	0.064
Incipient	Training	0.101	0.057
	Testing	0.089	0.058
CV,P_1, P_2,T			
All	Training	0.146	0.081
	Testing	0.145	0.079
Abrupt	Training	0.22	0.174
	Testing	0.28	0.229
Incipient	Training	0.038	0.023
	Testing	0.066	0.036
CV,P_1, P_2,X			
All	Training	0.117	0.064
	Testing	0.086	0.047
Abrupt	Training	0.151	0.113
	Testing	0.183	0.145
Incipient	Training	0.0113	0.008
	Testing	0.026	0.0106
CV,P_1,T,X			
All	Training	0.45	0.061
	Testing	0.118	0.062
Abrupt	Training	0.149	0.105
	Testing	0.178	0.127
Incipient	Training	0.006	0.005
	Testing	0.022	0.009
CV,P_2,T,X			
All	Training	0.1102	0.061
	Testing	0.111	0.063
Abrupt	Training	0.152	0.11
	Testing	0.144	0.10
Incipient	Training	0.0184	0.015
	Testing	0.0192	0.016
P_1, P_2,T,X			
All	Training	0.125	0.06
	Testing	0.030	0.021
Abrupt	Training	0.140	0.108
	Testing	0.141	0.112
Incipient	Training	0.014	0.006
	Testing	0.005	0.004
CV,P_1, T			
All	Training	0.134	0.082
	Testing	0.167	0.098
Abrupt	Training	0.324	0.24
	Testing	0.348	0.289
Incipient	Training	0.036	0.022
	Testing	0.076	0.035
P_1, T,X			
All	Training	0.134	0.084
	Testing	0.110	0.0702
Abrupt	Training	0.16	0.11
	Testing	0.15	0.10
Incipient	Training	0.01171	0.006
	Testing	0.011	0.0083
CV,P_1,X			
All	Training	0.112	0.074
	Testing	0.144	0.093
Abrupt	Training	0.146	0.122
	Testing	0.168	0.140
Incipient	Training	0.011	0.0074
	Testing	0.009	0.0076
P_1, P_2,X			
All	Training	0.122	0.061
	Testing	0.097	0.057
Abrupt	Training	0.163	0.118
	Testing	0.174	0.114
Incipient	Training	0.0050	0.0036
	Testing	0.018	0.0066
P_1, P_2,T			
All	Training	0.156	0.105
	Testing	0.203	0.137
Abrupt	Training	0.298	0.266
	Testing	0.319	0.265
Incipient	Training	0.147	0.121
	Testing	0.159	0.134
P_2,T,X			
All	Training	0.119	0.066
	Testing	0.101	0.054
Abrupt	Training	0.148	0.102
	Testing	0.149	0.110
Incipient	Training	0.20	0.017

	Testing	0.033	0.019
CV,P_2,X			
All	Training	0.116	0.061
	Testing	0.101	0.049
Abrupt	Training	0.145	0.115
	Testing	0.171	0.145
Incipient	Training	0.0246	0.020
	Testing	0.0226	0.019
CV,P2,T			
All	Training	0.136	0.089
	Testing	0.181	0.122
Abrupt	Training	0.22	0.166
	Testing	0.28	0.239
Incipient	Training	0.065	0.041
	Testing	0.046	0.0375
CV,P_1, P_2			
All	Training	0.175	0.10
	Testing	0.213	0.145
Abrupt	Training	0.307	0.258
	Testing	0.292	0.243
Incipient	Training	0.046	0.026
	Testing	0.052	0.028
CV, T,X			
All	Training	0.125	0.075
	Testing	0.0498	0.039
Abrupt	Training	0.146	0.113
	Testing	0.131	0.099
Incipient	Training	0.027	0.016
	Testing	0.016	0.014

It can be noted that these results may also be utilized for decision making in case of sensor failure. For example if the temperature sensor is out of order or is picking up noise, then fault diagnosis can be carried out by using other combinations of sensors with the following levels of errors as shown in Table 3.

Table 3: Results for Selection of Alternative Sensors for modeling Flow in Abrupt and Incipient Fault Conditions in absence of Temperature Sensor data

		RMSE	MAE
CV,P_1, P_2,X			
All	Training	0.117	0.064
	Testing	0.086	0.047
Abrupt	Training	0.151	0.113
	Testing	0.183	0.145
Incipient	Training	0.0113	0.008
	Testing	0.026	0.0106
CV,P_1,X			
All	Training	0.112	0.074
	Testing	0.144	0.093
Abrupt	Training	0.146	0.122
	Testing	0.168	0.140
Incipient	Training	0.011	0.0074
	Testing	0.009	0.0076
P_1, P_2,X			
All	Training	0.122	0.061
	Testing	0.097	0.057
Abrupt	Training	0.163	0.118
	Testing	0.174	0.114
Incipient	Training	0.0050	0.0036
	Testing	0.018	0.0066
CV,P_2,X			
All	Training	0.116	0.061
	Testing	0.101	0.049
Abrupt	Training	0.145	0.115
	Testing	0.171	0.145
Incipient	Training	0.0246	0.020
	Testing	0.0226	0.019
CV,P_1, P_2			
All	Training	0.175	0.10
	Testing	0.213	0.145
Abrupt	Training	0.307	0.258
	Testing	0.292	0.243
Incipient	Training	0.046	0.026
	Testing	0.052	0.028

It can be seen that the best model for abrupt faults in the absence of temperature data would be obtained by using either CV,P_1 and X or CV,P_2 and X, whereas if the fault is of incipient type, P_1, P_2 and X should be used.

III. CONCLUSION

This research work is expected to be of enormous value for practical applications in various industrial segments such as food processing, chemical, petro-chemical, cement, steel, power and desalination industries etc to name a few.

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] Vesanto J., “Neural network tool for data mining: SOM Toolbox”, In Proceedings of Symposium on Tool Environments and Development Methods for Intelligent Systems, Oulu, Finland, Oulunyliopistopaino, 2000, pages 184–196.

[4] Metenidis M. F., Witczak M., Korbicz J., “A Novel Genetic Programming Approach to Nonlinear System Modelling: Application to the DAMADICS Benchmark Problem”, Engineering Applications of Artificial Intelligence 17, 2004, 363–370.

Brief Biography of Author

Dr Tarun Chopra has obtained B.E.(Electrical Engg) from prestigious M.B.M. Engineering College Jodhpur in 2000 , GATE Scholar, M.E. (Electrical Engg) from B.I.T.Mesra in 2007 & Ph.D. (Electrical Engg) from M.B.M. Engineering College Jodhpur in 2011.

He is working as Associate Professor, Department of Electrical Engineering, Govt Engineering College Bikaner(India) since 2007.

His area of interest includes Intelligent Fault Diagnosis using Perception based computing in Control Systems.