Graphical User Interface Aided Online Fault Diagnosis of Electric Motor - DC Motor Case Study

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***Abstract*—This paper contains graphical user interface (GUI) aided online fault diagnosis for DC motor. The aim of the research is to prevent system faults. Online fault diagnosis has been studied. Design of fault diagnosis has two main levels: Level 1 comprises a traditional control loop; Level 2 contains knowledge based fault diagnosis. Fault diagnosis technique contains feature extraction module, feature cluster module and fault decision module. Wavelet analysis has been used for the feature extraction module. For the feature cluster module, fuzzy cluster has been applied. Faults effects are examined on the system using statistical analysis. In this study Fault Diagnosis technique obtains fault detection, identification and halting the system. In the meantime graphical user interface (GUI) is opened when fault is detected. GUI shows the measurement value, fault time and fault type. This property gives some information about the system to the personnel. As seen from the simulation results, faults can be detected and identified as soon as fault appears. In summary, if the system has a fault diagnosis structure, system dangerous situations can be avoided.**

***Index Terms*—wavelet analysis, fuzzy logic control, fault diagnosis, graphical user interface**

I. INTRODUCTION

If a fault is not detected, it may cause failure. In automatic processes, faults often cause undesired reactions and shut-down of a controlled plant and the consequences could be damage to technical parts of the plant, to the personnel or to the environment [1].

Importance of fault diagnosis, from a practical point of view, raises very interesting and challenging research directions [2]. In this respect, it is worth noting that the diagnosis of the faults will be useful.

Fault diagnosis task can be accomplished using analytical and functional information about the system using a mathematical model of the plant [2]. The main idea is the generation of residuals, signals that reflect the difference between nominal and faulty system. The residuals are usually generated using analytical approaches, such as observers, parity equations or parameter estimation. These methods make use of parameter estimation techniques, state estimation techniques and parity space concepts, etc. [2]. The traditional model-based fault diagnosis methods cannot guarantee satisfactory performance because of modeling errors effects. This procedure avoids physical redundancy where more than one sensor is used to get fault indicators [3]. But physical redundancy has two major restrictions: high-cost and more occupied space. For this reason, knowledge based methods have been developed as a combination of the analytical approaches with artificial intelligence (AI) methods e.g. neural networks, fuzzy logic, neuro-fuzzy schemes, evolutionary programming, expert system, genetic algorithms, etc. [4, 5]. Knowledge-based methods are sometimes called model-free or qualitative methods [6]. In this study, model free fault diagnosis is used and fault diagnosis structure is integrated to the system as online.

Artificial Intelligence (AI) methods have numerous advantages over conventional fault diagnostic approaches. These techniques are easy to extend and modify and can be made adaptive by the integration of new data [5]. Hence, fuzzy cluster technique is used as knowledge based in this study. Wavelet analysis is used for feature extraction of the signal. Wavelet technique analyzes signals in time and frequency domains and gets the results to describe the character of the signals.

The paper is organized as follows: Section 2 describes the structure of fault diagnosis. The wavelet analysis is described in section 3. Section 4 describes the fuzzy logic control of dc motors, and finally, simulation results are provided.

II. FAULT DIAGNOSIS

Fault can take place in different parts of the controlled system. Open loop system can be separated into three parts: actuator, plant and sensor as illustrated in figure 1 [7].

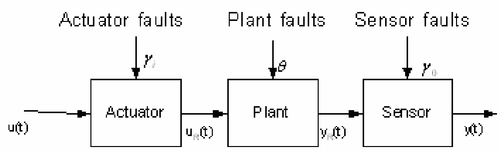

Figure 1. Open loop system.

As shown in Figure 1 there are three types of faults. These are presented below. Plant fault changes the dynamical input-output properties of the system. Sensor fault does not affect the plant properties, but the sensor readings have important errors. Actuator faults interrupt or modify the influence of the controller on the plant [3].

In this study sensor faults are taken into the consideration. Equation (1) shows the mathematical model of the sensor fault. γ_0 is the sensor fault, y(t) is the sensor output and yR(t) is the plant output for equation (1) .

$$y(t) = y_R(t) + \gamma_0 \tag{1}$$

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Sensor faults (γ_0) represent incorrect reading from the sensors that the system is equipped with. Sensor faults can also be subdivided into partial and total [8]. Total sensor faults produce information that is not related to value of the measured physical parameter. It can be due to broken wires, lost contact with the surface, etc. Partial sensor faults produce reading that is related to the measured signal in such a way that useful information could still be retrieved [8]. In this paper partial sensor faults are taken into consideration as additive and multiplicative types. Examples of sensor faults include loss of sensor signal, sensor drift, a sensor whose output has become stuck and a sensor whose output is unpredictable. In all these situations, the information coming out of the sensor is no longer representative of the true value of what is being measured by the sensor [9]. An inappropriate control may lead to system deadlock, capacity overflows, or may otherwise degrade system performance. Hence, the fault diagnosis becomes a more and more difficult process [10].

The structure of fault diagnosis which is used for this study is shown in Figure 2. Wavelet analysis and fuzzy cluster techniques are used. Wavelet analysis is used for feature extraction of the faults while the fuzzy cluster is used for knowledge base construction.

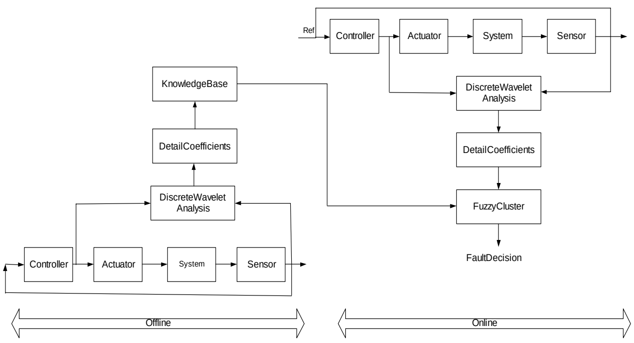

Figure 2. The structure of fault diagnosis.

III. WAVELET ANALYSIS

Faults cause changes in the response of measured signals, changes in time response and in frequency response for the system. Wavelet analysis is capable of detecting the change or transition in the signal [11]. Hence, wavelet analysis is preferred for this study. The main advantage of Wavelet Analysis (WA) as compared with Short-Time Fourier Transform (STFT) is that the size of the analysis window is not constant [12]. This property enables WA to zoom in on details. The traditional Fourier techniques cannot simultaneously achieve good localization in both time and frequency for a signal [12]. WA can be applied as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). The CWT uses a continuous range of scales and shifts at the expense of increased computational time, whereas the DWT uses a discrete range (in power of 2) of scales and shifts. DWT may be more beneficial in practical applications because of the shorter computational time, which is of the order of 2 times n by m (where n=number of scales and m=number of shifts) [13]. The operation of the wavelet transform is illustrated in Figure 3 [13]. At each level, the signal is separated using low pass and high pass filters into a "detailed" component, which are the high frequency components, and an "approximated" component, which is the low frequency component. The correlation between the signal and the wavelet at each level of scaling and shifting is called the wavelet coefficient [13]

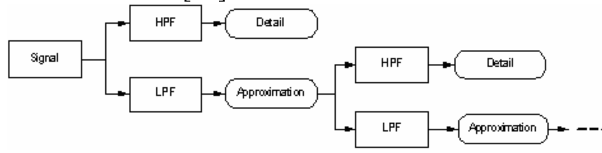

Figure 3. The operation of the wavelet transform.

In this study the Symmetrical Wavelet (Symlet) is used. Figure 4 shows the sym 2. The Symlet wavelets are near-symmetric and smooth [14]. Symlet wavelets show the orthogonal properties. Orthogonal wavelets performance is fine for numeric analysis [15] hence Symlet wavelet is preferred for this study.

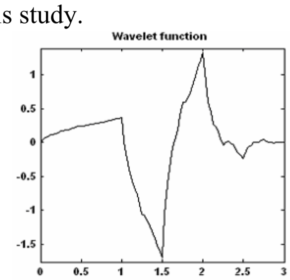

Figure 4. Symlet 2 wavelet.

IV. FUZZY LOGIC CONTROL OF DC MOTOR

This paper contains GUI aided Online Fault Diagnosis of electric motor. Electric motors play a very significant role in the safety and efficient operation of industrial plants. As a case study DC motor is examined. The resistance of the armature and its inductance are shown by R_a and L_a respectively in Figure 5a. The field circuit is represented by R_f and L_f in Figure 5b .

a) Armature circuit b) Field circuit

Figure 5. DC Machine.

Equation (2-3) obtained from Figure 5a and Figure 5b .

$$V_a = i_a R_a + L_a \frac{di_a}{dt} + e_c \tag{2}$$

$$v_f = R_f i_f + L_f \frac{di_f}{dt} \tag{3}$$

The related parameters of the system are given in table 1.

TABLE 1. PARAMETERS OF THE DC MOTOR

Description	Parameters	Value
The motor armature resistance	Ra	9 Ω
The motor armature inductance	La	0.018 H
The moment of inertia of the whole system	J	0.006 kg •m^2
The motor voltage constant	Kb	0.5 V •s/rad
The motor mechanical constant	Ki	0.5 V •m/A
The motor friction coefficient	B	0.006 N •m •s/rad

DC motor control is obtained with FLC. The goal of designed FLC in this study is to minimize the error. Surface of the FLC is showed in Figure 6.

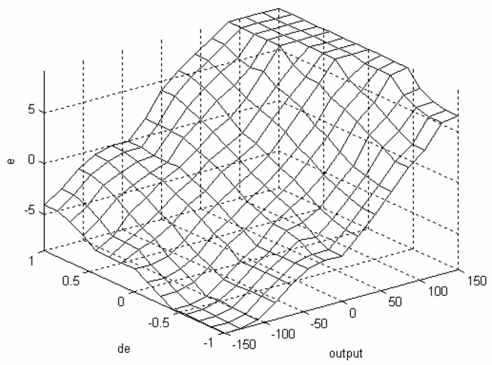

Figure 6. Surface of the FLC.

V. Simulation Results

Control of the system is provided by fuzzy logic controller. The reference value ω for dc motor was determined as 60 rad/sec. The key benefit of fuzzy logic controller is that it allows the operator to describe the system behavior relationship with simple if-then rules [16].

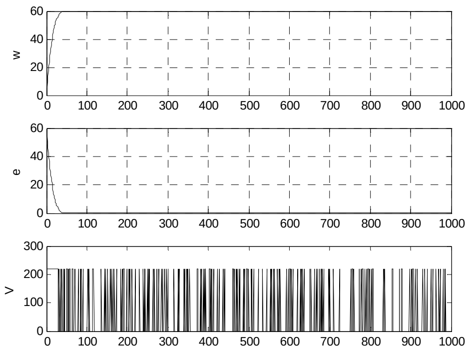

Figure 7. System response for the reference value.

As shown in Figure 7, reference value (ω) is obtained by FLC. Error (e) is nearly zero. Some sensor fault types have been applied to the system. Fault types and their status numbers are shown in Table 2.

TABLE 2. FAULT TYPES AND THEIR STATUS NUMBERS.

Status No	Fault type
#1	Normal
#2	Additive fault (+15)
#3	Multiplicative fault (x0.75)
#4	Additive fault (-8)
#5	Multiplicative fault (x1.15)

Five classes of process behavior are taken into consideration as faults (#1,#2,#3,#4,#5). Sensor fault start time is the 5^{th} sec for each fault in order to examine the features of the fault. The parameter values were taken from 1000 samples in 10 seconds. Measurement values which are taken by sensor are shown in Figure 8. As shown in Figure 8, sensor faults are clear at the 500^{th} sample. Measurement values show that speed value is at the reference value but in fact speed values for the DC motor are different because of the sensor faults.

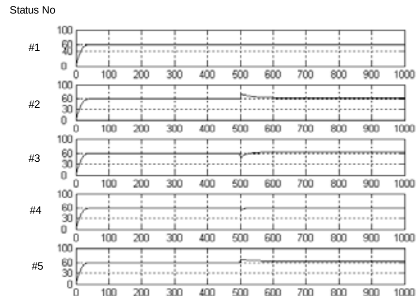

Figure 8. Measurement speed (ω) values for DC machine.

Figure 9 shows the effects of sensor faults for speed (ω), error (e) and voltage (V) for status no #2. Status no #2 is applied as an additive sensor fault. When speed values of Figures 9, 10, 11 and 12 compared with Figure 8 which contains speed measurement values it is seen that the values are different because of the sensor fault. On the other hand the error (e) of the system is nearly zero as shown in Figure 9, Figure 10, Figure 11, and Figure 12 because measurement values are being taken by sensor which has a fault. Nominal controller takes value information from the sensor and control signal is applied to the system according to the measurement values.

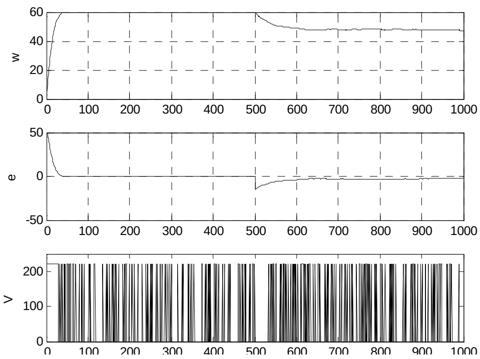

Figure 9. Effect of status no # 2.

Figure 10 shows the status no #3. This fault is applied to the sensor as a multiplicative fault. Speed value for DC machine is deviated because of the fault as shown in Figure 10. On the other hand, error value (e) is nearly zero because the sensor takes the speed value as 60 rad/sec but which is not.

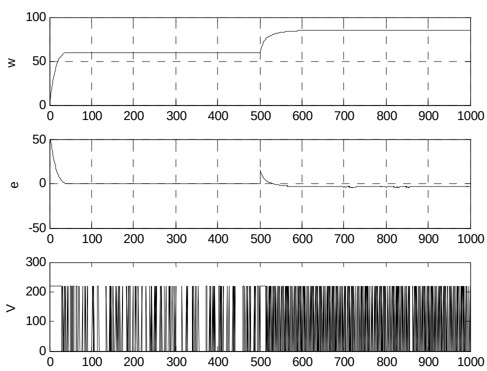

Figure 10. Effect of status no#3.

Figure 11 shows the status no #4. This fault is applied as an additive fault. Speed value for DC machine is deviated because of the fault as shown in Figure 11. On the other hand, error value (e) is nearly zero because the sensor takes the speed value as 60 rad/sec but which is not.

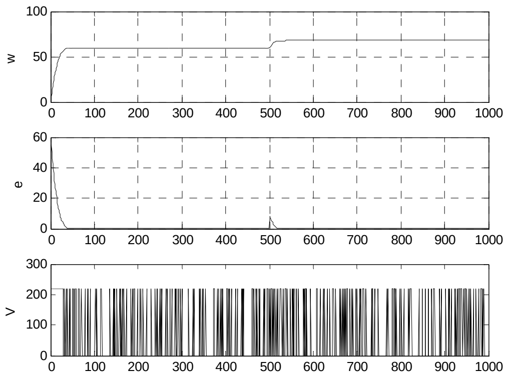

Figure 11. Effect of status no#4.

Figure 12 shows the status no #5. This fault is applied to the sensor as a multiplicative fault. Speed value for DC machine is decline because of the fault as shown in Figure 12. Voltage (V) is applied seldom to the system when fault occurs for status no #5 .

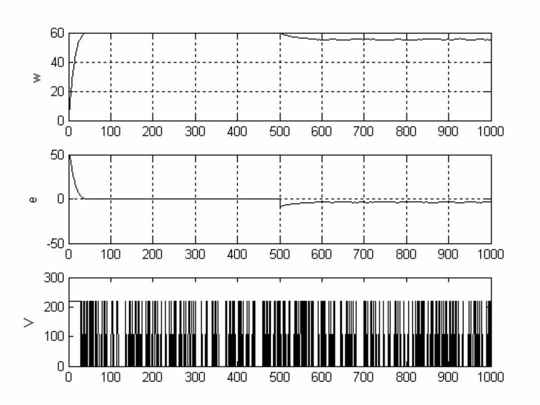

Figure 12. Effect of status no #5.

Figure 9, Figure 10, Figure 11 and Figure 12 show the fault effects for speed value. To abrogate of the fault effects, fault diagnosis technique will be added to the system. Thus when fault occur in the system, fault will be detected and identified so the system will be stopped.

Features of the faults are extracted using wavelet analysis for fault diagnosis constitution. Wavelet analysis is explained in section 3. The detail coefficients of faulty situations are shown in Figure 13.

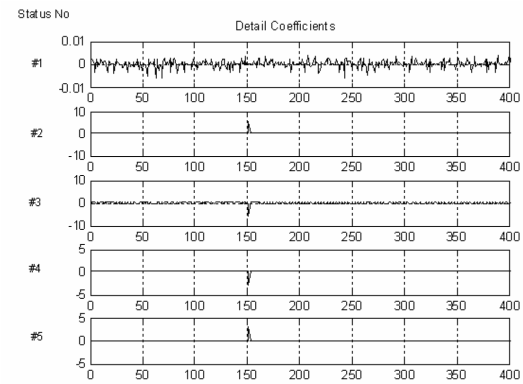

Figure 13. Detail Coefficients of measurement values.

Detail coefficients of the controller output are shown in Figure 14.

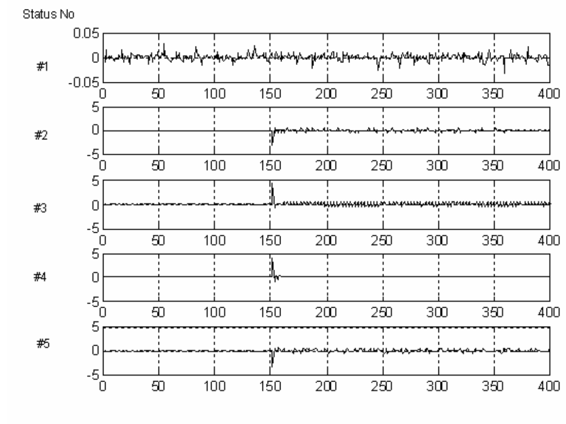

Figure 14. Detail coefficients of the controller output.

After obtained detail coefficients, fuzzy cluster will give the decision about the system has a fault or not as online in this respect it is important to give a decision about fault quickly. Fuzzy clustering can not only extract features from raw data directly**,** but also select the optimal feature sets or reduce the dimensionality of obtained features [17]**.** Fuzzy clustering is also playing an important role in the raw data domain as well as in transform domains [17]. Hence fuzzy cluster is used. At previous study Self Organizing Map (SOM) is used for classification [18, 19].

Fuzzy cluster is constructed using detail coefficients. Table 3 shows the boundaries values of detail coefficients for controller output and sensor output.

TABLE 3. BOUNDARIES VALUES OF DETAIL COEFFICIENTS FOR CONTROLLER OUTPUT AND SENSOR OUTPUT.

	Control inputs (min. values)	Control inputs (max. values)	Sensor output (min. values)	Sensor output (max. values)
#1	-0.0317	0.0291	-0.0060	0.0040
#2	-3.0887	0.6218	-0.0900	5.4664
#3	-0.6504	4.2922	-6.0089	0.0748
#4	-0.8948	4.0090	-3.2702	0.1053
#5	-3.4571	0.6317	-0.0960	3.2568

Fuzzy cluster for fault diagnosis is shown in Figure 15. The input variables are sensor output and control input. If a fault is detected, fuzzy cluster identifies the fault as which fault occurs in the system.

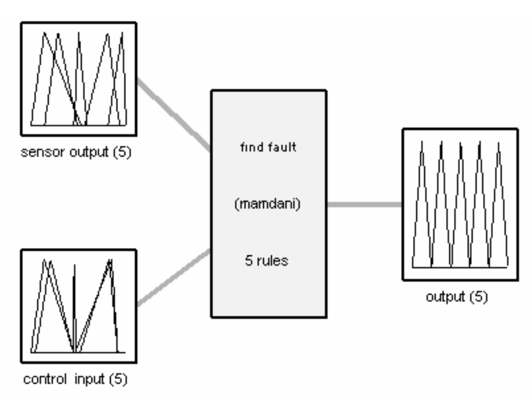

Figure 15. Fuzzy cluster for fault diagnosis.

MatLab-Simulink block diagram for online fault diagnosis is showed in Figure 16.

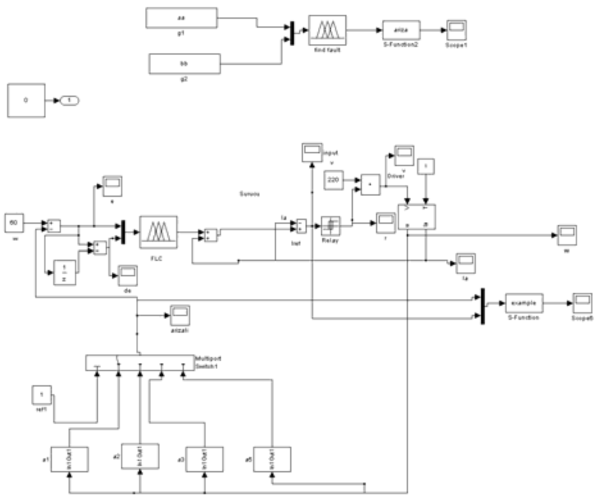

Figure 16. MatLab-Simulink block diagram for online fault diagnosis.

Fault diagnosis results are given in Figures (17-18-19-20). If fault diagnosis system structure detects and identifies a fault, this technique stops the system. In this way fault effects will be averted. Faults applied to the sensor at different times. Sample time is 10ms for all simulations. For Figure 17 fault is applied at the 3th second and it is detected and identified at the 3.06th second which means diagnosis just kept 0.06 second.

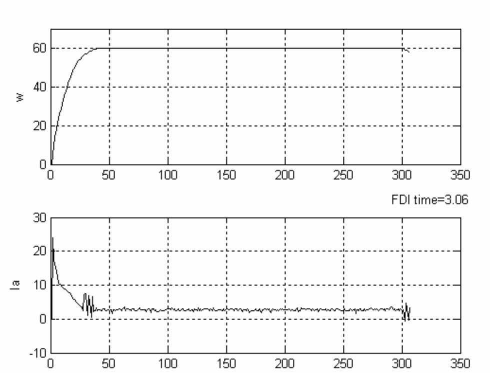

Figure 17. Fault is detected and identified as #2.

Figure 18 shows the status no #3 which is started at the 4th second and it is detected and identified at the 4.05 th second which means detection and identification just kept 0.05 second.

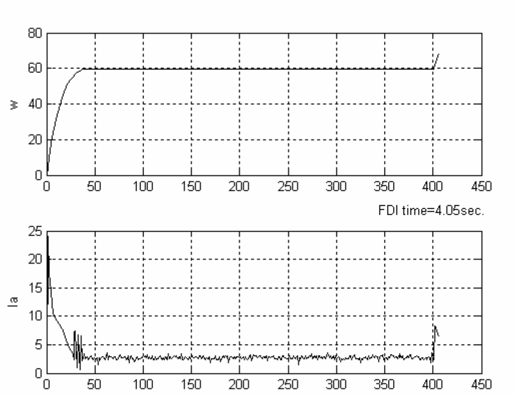

Figure 18. Fault is detected and identified as #3.

Fault is applied at 7th second and it is detected and identified at the 7.06 th second for Figure 19.

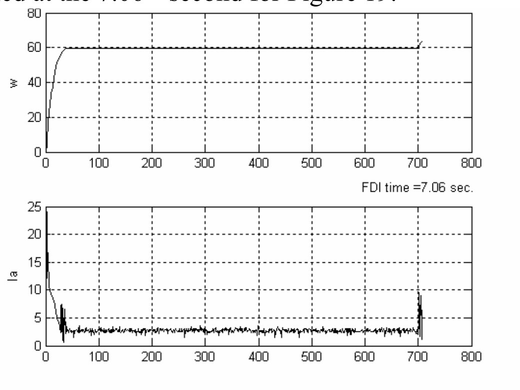

Figure 19. Fault is detected and identified as #4.

For Figure 20 fault is applied at the 10th second. Detection and identification just kept 0.05 th second.

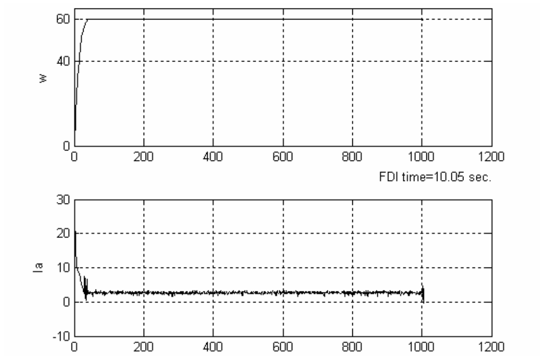

Figure 20. Fault is detected and identified as #5.

As shown in Figures (17-18-19-20) faults are detected and identified quickly. Additionally GUI is added to the system as a tool. Fault diagnosis tool consist of measurement value graphic, fault alarm, fault type and fault time. When the fault is detected user interface appears and gives the warning about the fault. If you want to see the details about faults like fault type, fault time and measurement value, result button is used. Figure 21 shows fault diagnosis tool.

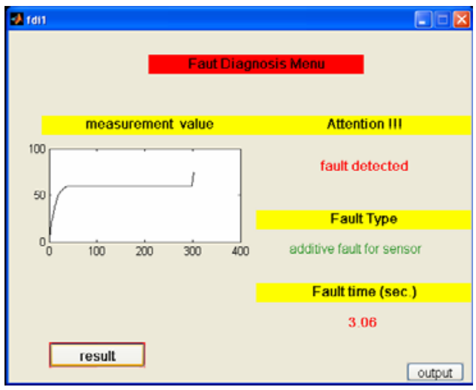

Figure 21. Fault diagnosis tool.

Fault diagnosis tool has been designed to simplify the work of the operator, monitoring the performance of the system. If fault diagnosis technique was not applied to the system, system would maintain to work but not at the reference point. The statistical analysis of the system working under faulty circumstances is shown in table 4.

System output is examined with statistical analysis as mean, median, range, standard deviation and maximum values.

TABLE 4. THE STATISTICAL ANALYSIS RESULTS FOR ALL STATUS

	Mean	Median	Maximum	Range	Standart deviation
# 1	59.14	59.80	59.83	59.83	4.708
# 2	53.59	54.25	59.82	59.82	6.916
# 3	71.27	59.82	85.25	85.25	13.79
# 4	63.08	59.82	67.81	67.81	6.574
# 5	57.05	57.12	59.82	59.82	4.902

Figure 22 shows differences between normal and the faulty conditions as visual graphic.

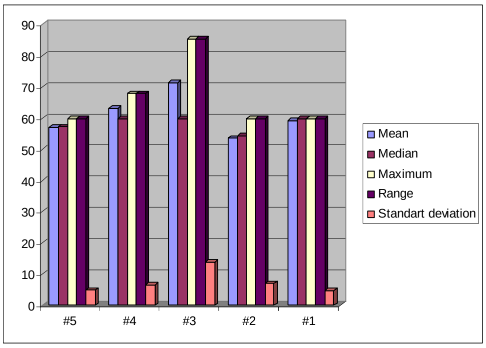

Figure 22. Statistical analysis effects of the system with faults.

Consequently, if the systems do not have a fault diagnosis structure, system will continue to work but not desired performance. As shown in Figure 22 values for mean, median, maximum, range and standard deviation are different and deviated from normal condition (#1). While the systems are working under faulty conditions, they can damage the operators even sometimes the environment. For this reason fault diagnosis technique should be integrated to the classical control systems.

VI. CONCLUSIONS

The traditional model-based fault diagnosis methods cannot guarantee performance satisfactory because of modeling errors effects so this study include model free fault diagnosis method. To reach the acceptable level at control performance is an important problem for control system for this reason diagnosis of the sensor faults will be useful in practice. This paper addresses online fault diagnosis with fuzzy cluster and wavelet analysis for DC motor. Feature extraction is constructed using wavelet analysis. Fuzzy cluster is applied. Examples of sensor faults include loss of sensor signal, sensor drift, and a sensor whose output has become stuck. In all of these situations, the information coming out of the sensor is not representative of the true value so it can be insert the system in a danger situation. A situation like that can cause the economical disadvantage, loss of time or can injure the personnel. For this reason to abrogate the fault effects, fault diagnosis technique should be added to the system. Thus when a fault occurs in the system, fault will be detected and identified so the system will be stopped. Additionally when fault is diagnosed, fault diagnosis tool which is constructed with GUI is emerged. Fault diagnosis tool includes the fault time, fault type, measurement value as a graphical. By means of the tool personnel can take the information about the system. Simulation results are satisfactory because faults are detected and identified in a short period of time which is important as much as fault diagnosis. Sometimes it can be late for the system at what time the fault is detected and identified.

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