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FPGA Realization of Fault Diagnostic Manufacturing Equipment using Fuzzy Expert System

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Abstract: The study describes the implementation of a fuzzy expert system based fault diagnostic system. The system is implemented into a Field Programmable Gate Array (FPGA) chip for fast design cycle. Real time faults diagnosis of manufacturing machinery equipment through software approach lacks in processing speed and slow interfacing with physical hardware. To overcome this increasing complexity of contemporary industrial processes and a wide range of hazards, a flexible, easy and shorter development time of intelligent fault diagnosis system is reuired. Fuzzy Logic System (FLS) is employed to process imprecise and uncertain system inputs. Highly parallelism execution into FPGA enhances the processing speed of fault diagnosis system and enabling the interfacing with hardware in real-time manner. Most of the synthesization tools are unable to simplify division operator and resulted in error in the synthesization of the system. Therefore, a division module is designed to enable the synthesization. The algorithm is based on repetitive substitution and bit shifting operations. Hardware implementation of the system into FPGA board enabled shorter time to design for both fault diagnostic system and manufacturing equipment. The results showed that the proposed FPGA performance required only 176 nsec of execution time for operating clock frequency of 50 MHz and 7594 logic elements into FPGA. This expert system aims to reduce the downtime for faulty manufacturing equipment and standardize the fault diagnostic procedures. The hardware implementation of fault diagnostic expert system into FPGA board brings advantages in ease of variability in the system and high speed processing due to hardware data parallelism.

Key words: Fuzzy logic, fault diagnosis, expert system, VLSI, FPGA, synthesis, HDL

INTRODUCTION

Many manufacturing industries production lines require 24 h operation per day, 7 days per week without any abnormal shutdown to satisfy critical market demands with mass production. Unfortunately, failure of manufacturing equipment is inevitable. Unscheduled stoppage of production line due to machinery failure causes huge damage. Trouble shooting malfunction equipment can be a long and complicated process. Typically the root cause of a fault is not obvious and having more than one symptom present. The fault could be resulted from the process components, process variables or even the control systems. There is also possibility where the fault condition is caused by multiple root causes at the same time. Fault diagnosis becomes more challenging as a result of constantly increasing complexity of contemporary industrial processes and the considerably wide range of hazards that may happen when a process is disrupted (Korbicz, 2004). This is due to the complexity in correlation between the symptoms and causes accompanied with the rapidly changing of the condition status. Numerous experiences and skills needed to be accumulated by the experts in the domain of the manufacturing equipment to perform the diagnosis effectively. Because, many diagnostic steps have to be carried out to eliminate the fault and bring the process back to the normal condition (Ye, 1996). However, experts are scarce, expensive and have natural shortcoming in deal with plenty of maintenance task. In addition, due to a wide variety of reasons, human expert may not be available on a reliable and continuing basis and not capable of remembering large amount of information (Folley and Hritz, 1987).

Expert systems are a set of software programs that emulate the reasoning process of a human expert to solve

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problems in a specialized domain. In the late 1960's expert systems began to emerge as a branch of Artificial Intelligence (AI). Various AI techniques are presently being applied in fault diagnosis process to enable replacement of expertise and improvement of the fault diagnostic system. By means of an expert system, the knowledge and experiences from the experts can be shared and reused with high consistency even an inexperienced worker is also able to decide competently about the state of the manufacturing systems and the equipment's behavior in further operation. To develop an expert system, knowledge base is the most important element as it determines the power and effectiveness of the expert system in decision-making. The knowledge base contains the expert's advice, experience, fault statistic data, troubleshooting guidelines and so forth. It represents domain specific knowledge in a specific form. It involves four activities to transfer expertise from an expert to the computer and then to the users which are knowledge acquisition, knowledge representation, knowledge inference and knowledge transfer (Turban, 1995). Expert system has been successfully applied in fault diagnosis by using association, reasoning and decision making processes to identify the root cause of a fault. AI techniques have been attempted in various research works to improve the accuracy and efficiency of fault diagnosis of machinery such as FLS, Artificial Neural Network (ANN) and hybrid AI techniques based fault diagnosis. ANN with learning ability and nonlinear problem modelling capability (Yang *et al*., 2002) allows maintenance personnel provide data into the system without understanding the inference process of neural network. Hence, new technicians are unable to understand and learn on how the faults arise from the problems. Slow convergence and lengthy time for training make ANN System unsuitable for a fast and on line machine diagnosis (Chowdhury *et al*., 2008). In another fuzzy modelling approach showed utilizing IF-THEN rules to interpret linguistic variables for determination of priorities and demonstrated its usefulness in fault diagnosis applications (Ramezani and Memariani, 2011). In many complex control system applications, FLS is preferably and more effective than by mathematical modelling of the control system. This is mainly due to their ability to deal with uncertainty reasoning and linguistic variables rather than mathematical modeling (Monmasson and Cirstea, 2007).

This research work has been carried out to develop and implement of Diagnostic Manufacturing Equipment Expert System (DMEES) into FPGA board by using FLS and expert system for a vertical turbine pump. The main purposes is to determine the root cause of a fault and help machine operator to cope with the fault happen and learn from the fault diagnosis procedures. Compared with the algorithmic approaches, fuzzy logic-based approach in a fault diagnosis system is more efficient as it enables the system to follow humans' ways of thinking in the fault diagnosing (Cintra *et al*., 2011). The system was first developed in MATLAB environment. Both the MATLAB codes and fuzzy logic toolbox were used to design the FLS. The results generated from both methods were compared. The diagnostic system also has been tested in MATLAB environment to develop the algorithm of entire fault diagnostic system. Next, the behavioural model of the system was developed using Verilog HDL. Simulation, synthesization and implementation of the system design have been done in sequence. RTL descriptions of the design were generated and checked for debugging and optimization purposes.

DEVELOPMENT OF DMEES USING FUZZY LOGIC IN MATLAB

To develop an expert system, knowledge base is the most vital element as it determines the power and effectiveness in decision-making process. A troubleshooting guide of a vertical turbine pump (Wu *et al*., 2012) was used to setup the knowledge base. It consists of 34 possible causes of faults which can be derived from 6 symptoms. The idea was based on establishment of average ranking number of all possible causes. It was ineffective and unable to handle imprecise information about the machinery condition. This research has made assumption on the high flow coefficient of the chosen device, resulted in only two important symptoms required for the deduction of type of cause of fault. The 34 possible causes of fault were categorized based on the location of fault by using fault tree analysis and finally only 9 possible types of causes were required for further diagnosis. The algorithm of the FLS and DMEES were developed in MATLAB. Mamdani Fuzzy Inference Model was chosen to design the FLS with 2 input variables (symptoms). Both symptoms are processed by the FLS as shown in Fig. 1, to obtain the sorted rank order of possible type of causes.

Fuzzification: The symptom liquid delivery capacity was described by linguistic terms of normal, low and very low while the symptom vibration was represented by linguistic terms of normal, moderate and high. Fuzzy sets for each linguistic variable were defined in trapezoidal membership functions. Therefore, the degree of membership function

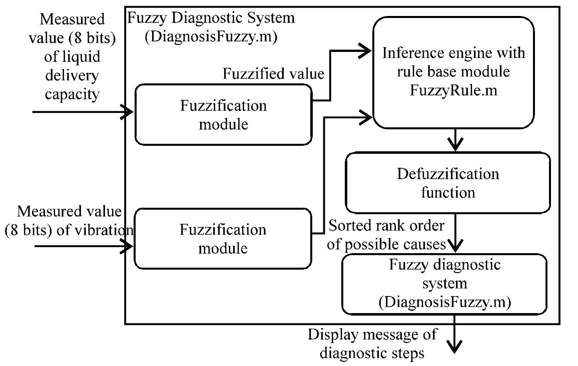


Fig. 1: Block diagram of Fuzzy Logic System in MATLAB environment

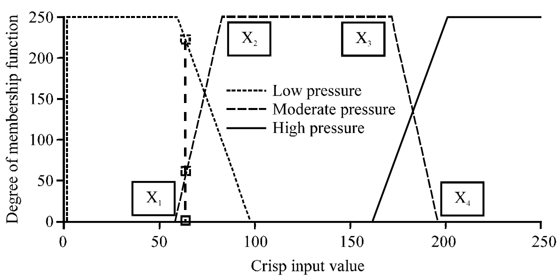


Fig. 2: Calculation of degree of membership for trapezoidal membership function

for a crisp input value in each fuzzy set can be determined. By assuming both symptoms conditions were acquired by sensors, processed and then converted into 8 bit digital signals, the input strength and the degree of membership function for both input variables can be represented from 00H to FFH (equivalent to 0-255 in decimal representation). This was done to enable the development and implementation of the functional model of the system into FPGA board. Each of the trapezoidal membership functions is mainly defined by 4 points. For example, as shown in Fig. 2, 4 points X_1, X_2, X_3 and X_4 are required to locate the degree of membership function of input variable pressure. Equation 1 is used to calculate the degree of membership function for a crisp input value

$$\text{Degree of membership function} =$$

$$x: \begin{cases} 0 & x \le X_1 \\ (x-X_1)\dfrac{255}{X_2-X_1} & X_1 < x < X_2 \\ 255 & X_2 \le x \le X_3 \\ 255-(x-X_3)\dfrac{255}{X_4-X_3} & X_3 < x < X_4 \\ 0 & x \ge X_4 \end{cases} \quad (1)$$

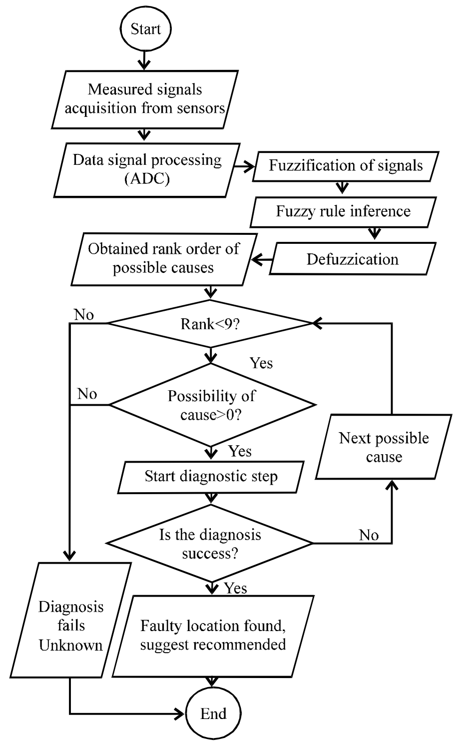


Fig. 3: Flowchart of fuzzy rule-based expert system for fault diagnostic system

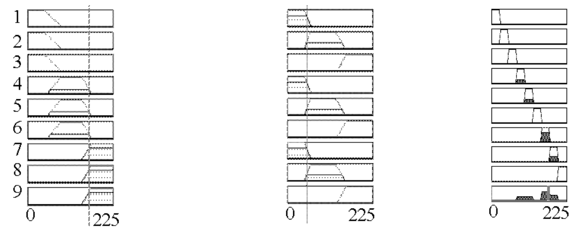
Fuzzy inference mechanism: By using grid-partitioning matrix, 9 fuzzy rules were developed from the membership functions of both symptoms. By referring to the fuzzy rule base, fuzzy inference mechanism decides which rules to be fired based on the input strength. The conjunction of the fuzzy rules antecedents are evaluated by using AND logical operator.

Defuzzification: All the outputs from rules needed to be combined into a single value through defuzzification process. The defuzzification technique used is Largest of Maximum (LOM) which returns a possible type of cause with largest possibility. To enable the fault diagnosis system covers other causes with lower possibilities, the output of defuzzification is also appended with other type of causes with lower possibilities value sorted in descending order.

As shown in Fig. 3, once the sorted type of causes obtained from FLS, the expert system for fault diagnostic system is started. Diagnostic steps for all 9 possible types of causes of fault in the vertical turbine pump are arranged by using selection control mechanism. Every type of causes has several diagnostic steps which are required to be executed and acquire further analysis data, in order to locate the root cause of the failure. Forward chaining is

Table 1: Simulation comparison of results from MATLAB and fuzzy logic toolbox

Input	MATLAB code simulation result		Rule evaluation from MATLAB fuzzy logic toolbox		
			Liquid delivery capacity = 184	Vibration = 58	Causes = 196
LiqDel = 10111000 (184)	>>Fuzzy test (184,58) ans =				
Vibrate = 00111010 (58)	1	0			
	2	0			
	3	0			
	6	0			
	9	0			
	4	63.7500			
	5	63.7500			
	8	89.2500			
	7	165.7500			



the inference mechanisms used in the expert system. Presence of any fault is checked by the encoded rules in the knowledge base. The inference engine will move forward to search the conclusion in terms of the rule that was used to deduce it.

SIMULATION RESULTS IN MATLAB

The simulation result of FLS in MATLAB as shown in Table 1, demonstrated the type of causes arranged in ascending order with its possibility in the right column. By inserting 80 and 145 as the input value of liquid delivery capacity and vibration, respectively the defuzzified values obtained are type 5 and type 2 possible causes with possibility value of 127.5 and 102, respectively. As possible cause type 5 is shaft problem, therefore the diagnostic steps for shaft problem will be carried out first. Diagnostic steps and further evaluation of other input value were displayed on the MATLAB command window where the fault diagnosis system able to acquire measurements from any related sensors or user input. A remedy action will be displayed once the root cause of the faulty conditions is able to be located through the analysis by DMEES.

DEVELOPMENT OF DMEES IN VERILOG

Fuzzification: Behavioral Model of DMEES was developed by using Verilog HDL. The development of fuzzification module was similar to the MATLAB one. Each membership function requires 4 point values to form the trapezoidal shape membership function. The calculation of the degree of membership function is based on Eq. 1.

Fuzzy inference mechanism: Similar to system design in MATLAB, minimum function was used to build the conjunction between 2 membership function values in fuzzy rules.

Defuzzification: In the defuzzification module, Bubble-Sort algorithm was applied to sort the output fuzzy set causes in descending order while in the same time works to apply for LOM Method of defuzzification.

This simple sorting algorithm works well for 9 variables by repeatedly stepping through the list to be sorted comparing each pair of adjacent items and then swapping them if they are in the wrong order.

The expert system is developed by using forward chaining inference mechanisms to reach the conclusion (root cause) of the fault diagnosis process. The rules have been encoded in either if-else or case conditional statements.

SIMULATION RESULTS IN VERILOG

DMEES was able to be tested with various symptoms conditions. The functional and timing simulation was performed by using MultiSim-Altera. Division operation was required in fuzzification module to calculate the degree of membership function. However, in Verilog HDL, division operator is unable to be synthesized by most of the synthesis tools. The division operation algorithm developed was continuous comparison between the dividend and the divisor, subtraction of the dividend from the divisor and then shifting of quotient for every bits of dividend. The dividend was extended to 21 bits initially to add accuracy of the division up to four decimal places. The decimal places will be rounded off if the values of five least significant bits are larger than 0.40625 (0.01101 in binary representation). This was done to reduce the round-off error in the fuzzification process. The registers rule contains the output fuzzy set values before the aggregation and defuzzification process. The floating point values were rounded off into integer and compared with the output fuzzy set values simulated in MATLAB environment. The result was satisfying as every output fuzzy set values were similar. Next, the entire FLS was tested as well. The aggregated output fuzzy sets were defuzzified into an array of values in descending order. The simulation results of FLS are shown in Fig. 4.

LOGIC SYNTHESIS OF DMEES

Logic synthesis is a process of converting a higher level of abstraction to a lower level of abstraction for design implementation purpose. The design of behavioral model of the system in verilog HDL was converted into

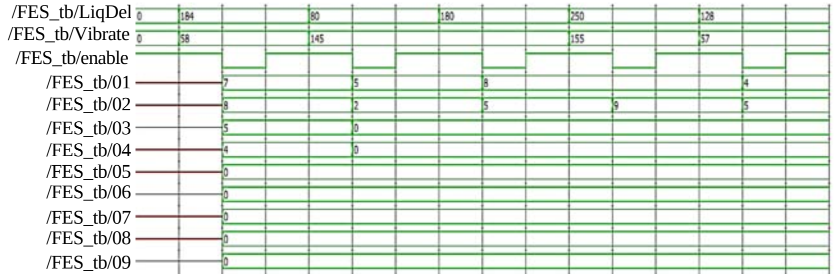


Fig. 4: Simulation waveform of fuzzy inference system module from MultiSim Altera

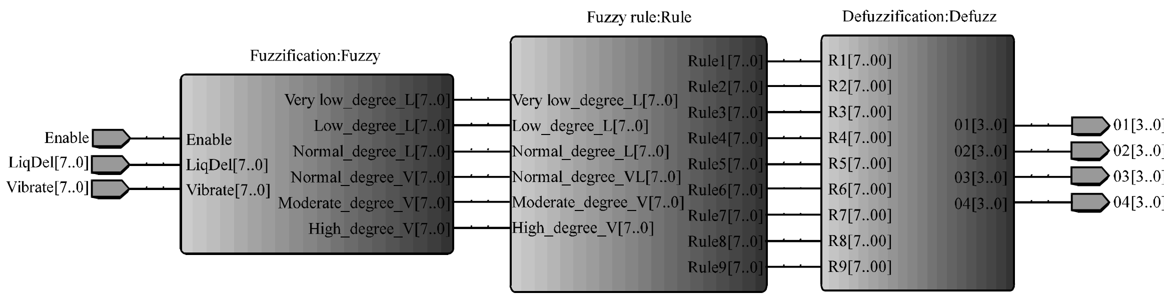


Fig 5: RTL view of Fuzzy Logic system module in Altera Quartus II

gate level netlist. This was done by using synthesis tool, Quartus II Integrated Synthesis (QIS). The Register Transfer Level (RTL) viewer and technology map viewer were used to view the initial and fully mapped synthesis results during the debugging, optimization and constraint entry processes. The result of the synthesis contains details gate level netlists for the entire functional module of the system. The top module of the FLS, "FuzzyExpertSystem" was synthesized and RTL view was generated as in Fig. 5. The full compilation of the designed system generated a timing analysis data to check the performance of the designed system. The maximum time for clock to output for the designed system is 176 nsec in operating clock frequency of 50 MHz. It is the time from the input variables are inserted until the generation of results. In addition, the total logic elements used in the FPGA board is 7594 units, equivalent to 23% of the resources available in Altera DE2 FPGA board.

IMPLEMENTATION OF DMEES INTO FPGA BOARD

The efficiency and reliability of the fault diagnosis system can be improved by embedding real-time process variables monitoring into the Knowledge-Based Fault Diagnosis Method. Hence, FPGA has been chosen to enable the system to be intimately mapped for hardware implementation. FPGA provides both the performance benefits of ASICs and the flexibility of processor. The hardware implementation of FLS is better than the equivalent software implementation executed on a processor due to its high parallelism processing performance especially in real-time and embedded applications (Chowdhury *et al*., 2011). The netlists was fitted into the actual FPGA architecture by using place and route tools. Bit streams were generated by assembly tool for FPGA to enable the reconfiguration of the target FPGA boards over the JTAG connection. The values of the sensors data can be entered by using logic switches in the FPGA board which represent the pump conditions. Initially, FLS processes the inputs to obtain the most probable type of cause of failure in the pump. The outputs shown in the 16 red LEDs represent the 4 most probable types of causes as shown in Fig. 6. Next, the diagnosis procedures for the most probable type of causes will be shown in LCD to guide users to perform corrective action on the pump. During diagnosis procedures, certain condition measurement signals may be needed to be derived from sensors or obtained from user's observation. Once the expert system locates the fault by processing the input signals, the fault diagnosis process is completed and the red LED will light on. However, if the whole set of fault diagnosis procedures for the most probable type of cause has been carried out and still unable to locate the fault then the fault diagnosis procedures for next probable type of cause will be performed. The results for 5 sets of input values as shown in Table 2 were found to be similar for various platforms. It can be concluded that the algorithm is works throughout various platforms from MATLAB simulation to hardware implementation into FPGA board.

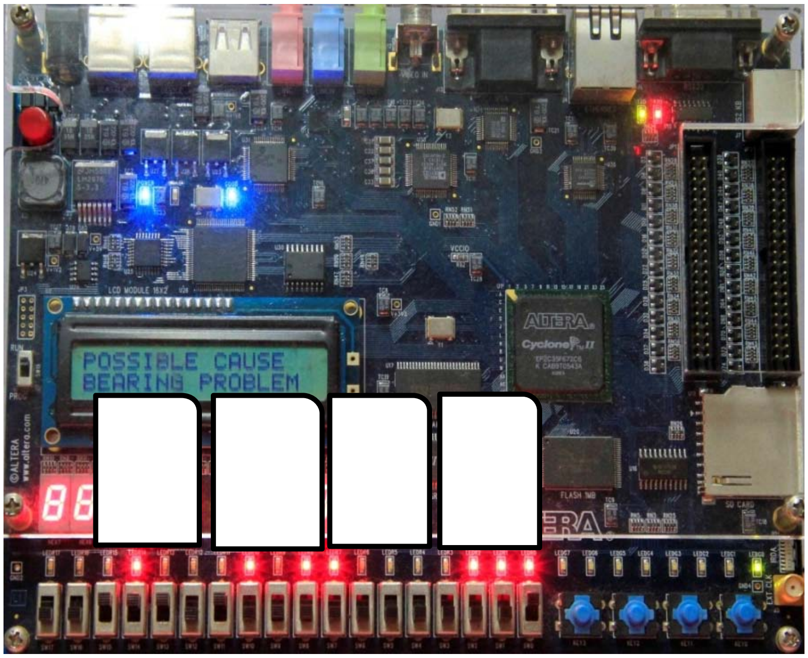


Fig. 6: Results obtained from system implementation using FPGA board (Altera DE2 Board)

Table 2: Comparison between MATLAB, Verilog HDL and FPGA implementation

	Result (top 4 possible type of causes in descending order)		
Inputs	MATLAB	Verilog HDL simulation	Implementation into FPGA
184, 58	7, 8, 5, 4	7, 8, 5, 4	7, 8, 5, 4
80, 145	5, 2	5, 2	5, 2
180, 145	8, 5	8, 5	8, 5
250, 155	8, 9	8, 9	8, 9
128, 57	4, 5	4, 5	4, 5

CONCLUSION

Timely and accurate equipment malfunction diagnosis can be a key to the success of the manufacturing process. The algorithm of the FLS and expert system were successfully applied into the fault diagnosis system and implemented into FPGA board to locate the root causes of the fault in manufacturing equipment. A division algorithm for the use in fuzzification process has been developed to enable synthesization of the DMEES. The overall system in FPGA board required only 7594 logic elements and 176 nsec with operating clock frequency of 50 MHz to process the symptoms acquired into determination of the possible type of causes. The simulation and FPGA implementation tests on the DMEES appeared to be similar proved the feasibility of the hardware implementation of the designed algorithm into FPGA board. The designed system can be fabricated into Application Specific Integrated Circuit (ASIC) in future.

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