Research Article

A Soft Computing Approach to Crack Detection and Impact Source Identification with Field-Programmable Gate Array Implementation

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The real-time nondestructive testing (NDT) for crack detection and impact source identification (CDISI) has attracted the researchers from diverse areas. This is apparent from the current work in the literature. CDISI has usually been performed by visual assessment of waveforms generated by a standard data acquisition system. In this paper we suggest an automation of CDISI for metal armor plates using a soft computing approach by developing a fuzzy inference system to effectively deal with this problem. It is also advantageous to develop a chip that can contribute towards real time CDISI. The objective of this paper is to report on efforts to develop an automated CDISI procedure and to formulate a technique such that the proposed method can be easily implemented on a chip. The CDISI fuzzy inference system is developed using MATLAB's fuzzy logic toolbox. A VLSI circuit for CDISI is developed on basis of fuzzy logic model using Verilog, a hardware description language (HDL). The Xilinx ISE WebPACK9.1i is used for design, synthesis, implementation, and verification. The CDISI field-programmable gate array (FPGA) implementation is done using Xilinx's Spartan 3 FPGA. SynaptiCAD's Verilog Simulators—VeriLogger PRO and ModelSim—are used as the software simulation and debug environment.

1. Introduction

Crack detection and impact source identification in materials is a renowned problem found in variety of commercial and military applications like beams, bridges, turbines, pavements, armor plates, vehicle body plates, bones, teeth, and so on. This long-standing interest in development of CDISI is evident from variety of methods proposed in the literature [1–33]. Ultrasonic guided waves are used for the crack detection [1, 2]. The crack detection is done by measuring lamb wave signals using the dual PZT transducers [3]. Wireless inductively-coupled transducers are used for the crack detection [4]. The wave velocities of concrete are measured by the portable transient elastic wave system to track the health of concrete [5]. Automation for different crack detection and impact source identification methods is lately carried out

in the literature using soft computing and VLSI techniques. Image processing techniques are used for the crack detection [6, 7]. One of the most effective tools to deal with complex problems with lack of certainty, accuracy, and absolute truth is the soft computing. Zadeh [8] describes soft computing "*Soft computing is tolerant of imprecision, uncertainty, partial truth, and approximation than the traditional Hard Computing. The role model for soft computing is the human brain.*" A fuzzy inference system [9] is developed to predict location and depth of the crack of a cracked cantilever beam structure in a close proximity to the real results. A hybrid artificial intelligence technique with fuzzy-neuro controller is used to detect the crack with its location in cantilever beam [10]. Fuzzy logic and expert system techniques are efficiently used in evaluation of pavement distress like cracking [11]. A genetic fuzzy system [12] is used for crack density and crack location
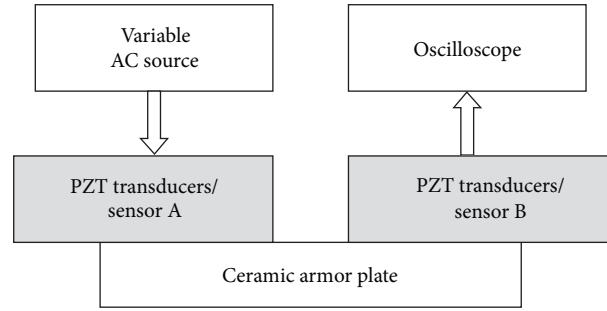
FIGURE 1: CDISI: crack detection test system circuit.

detection. The genetic fuzzy logic system [13] is used as method for automatic rule generation in fuzzy systems for structural damage detection. Reference [14] has presented a comprehensive structural fault detection method using fuzzy logic which is better suited to tolerate noise and uncertainty. A fuzzy rule-based system [15] is developed for the blade of a BO-105 helicopter rotor modeled as a cantilever beam and demonstrated that the fuzzy system performs accurately even in the existence of noisy data. The sensitivity of the modal frequencies and other parameters to a crack increases when the crack is near the sensors and decreases as the crack moves away, thus a modular neural network architecture [16] is presented as a nondestructive method for health monitoring of structures. The issue of uncertainty in material properties in structural damage detection with fuzzy logic is addressed by [30–33], with use of the fuzzy cognitive maps [30] used to solve this problem. Recently Meitzler et al. [1] have proposed an ultrasonic crack detection system, which uses transducers to detect the crack in metal armor plates. The existence of cracks is determined by comparing the output voltage waveforms with those of an undamaged plate manually using metrics.

NDT of an object determines its usefulness without ruining it to avoid its intended use. A CDISI problem is quite important to issues related to the security and safety of soldiers as it affects the armored vehicles' body plates and soldier's body armor on the battlefield. The NDT for CDISI accomplishes to perk up the reliability by assuring the quality level of armor material and operational readiness of armored vehicles and soldier's body armor plate prior to or during its day-to-day use. A CDISI system for armor plates is presented as a new soft computing method based on the fuzzy logic component. The FPGA implementation [1] of CDISI fuzzy inference system is done with an intention to embed it on a chip designed for a CDISI handheld device. Our approach uses the theory of soft computing to develop a model supported by VLSI design to determine the following metrics.

(1) Nature of plate: It is diagnosed to be in one of the four possible states like unknown, undamaged, slightly damaged, and damaged. The system generates *degree of crack* value in the range of [0, 1] where 0 represents an unknown state and 1 represents a damaged plate.

As the *degree of crack* value increases, the amount of crack in the plate also increases.

(2) Source of impact: The CDISI system currently recognizes two different sources of impact. This can be expanded for incorporation of a larger range of sources.

This paper is organized in the following manner. Section 2 focuses on the literature review and discusses the CDISI system description. Section 3 discusses the fundamental theory of fuzzy systems, fuzzy models, and fuzzy logic-based modeling techniques for CDISI. The proposed CDISI fuzzy inference system is given in Section 4. Section 5 presents FPGA implementation of CDISI system. An integrated approach of CDISI system which is based on the Fuzzy model and FPGA implementation is the topic of discussion in Section 6. Finally Section 7 concludes the paper.

2. CDISI System Description

Crack detection and impact source identification has been a widely studied problem in the literature using NDT approaches. The work of Meitzler et al. [1] is reviewed here for the ready reference. An ultrasonic crack detection system [1] for ceramic vehicle body armor support system (VBASS) plates as shown in Figure 1 uses two piezoelectric lead zirconate titanate (PZT) transducers attached with ceramic plate to be tested for the crack. Generally transducers are used to transmit energy from one type to another. Here they are used to stimulate and measure the resonances mode of rectangular ceramic armor plates in 50–300 kHz range of frequencies. PZT transducer/sensor A is connected to the variable AC source, and the PZT transducer/sensor B is connected to the oscilloscope for transmitted energy and excited vibrational mode analysis. The alteration in the mechanical structure or presence of cracks is determined by comparing the output voltage waveforms with those of an undamaged plate manually using metrics.

The impact source identification system consists of a ceramic plate [17, 18] as shown in Figure 2. The two sensors, sensor A and sensor B, are positioned on two sides of the ceramic plate which sense the acoustic emissions from submicron cracking caused by the hitting pressure. These
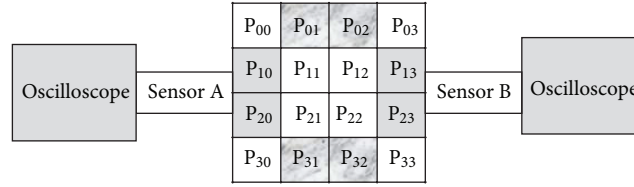
FIGURE 2: CDISI: impact source identification test system circuit.

sensors read the waveforms when the plate is hit by the source. The data acquisition system (DAS) extracts data from these waveforms. The location being hit on the plate affects the decision of impact source identification, so it has 16 parts where the source can be hit. These parts are labeled P_{00} to P_{33} as seen in Figure 2. The accuracy of the identification of the source of impact depends on the part number being hit by a source.

An automated procedure for the CDISI is proposed, which reads the waveforms from the sensors A and B in the test circuits seen in Figures 1 and 2 with the help of a DEWESoft data acquisition [19] system. The various parameters extracted from the CDISI system waveforms are frequency, average RMS, standard deviation, RMS value, peak value, median, mode, and FFT value. After systematic study of parameters it was noticed that some of these parameters are instrumental in the process of decision making towards *conclusion* = {*Nature of plate, Source of Impact*} and some are redundant. The unique parameters extracted from sensors A and B for the CDISI assessment are input frequency, average RMS, standard deviation, location index, Arms, Amax, Brms, and Bmax. The Arms and Brms are the RMS value for sensors A and B. Amax and Bmax are the peak value for the sensors A and B. The details of the input and output parameters of the CDISI are

Input Parameters

$$= \{\text{Input Frequency, Average RMS, Std. Deviation,}$$

$$\text{Location Index, Arms, Amax, Brms, Bmax}\}, \tag{a}$$

$$\text{Output Parameters} = \{\text{Nature of Plate, Source of Impact}\}, \tag{b}$$

Nature of Plate

$$= \{\text{Unknown, Undamaged, Damaged, Slightly Damaged}\}, \tag{c}$$

Source of Impact

$$\tag{d}$$
$$= \{\text{SourceType1, SourceType2, SourceUnknown}\}.$$

The CDISI test circuits as shown in Figures 1 and 2 generate a sufficiently large database for {Input Parameters, Output Parameters}. This database is influential in defining fuzzy relation between the inputs and output parameters.

In practice the time and frequency domain analysis of the sensor waveforms is used for CDISI, which many times turns out to be very expensive. To the best of authors knowledge fuzzy logic is the best candidate to express the relation between the input and the output parameters, due to the lack of strong mathematical model to represent this system. CDISI fuzzy system outperforms the conventional comparison method involving human error due to manual comparison of the waveforms with that of an ideal plate and the known source of impact. The CDISI fuzzy inference system is a fast, reasonably priced fault-diagnosis solution in the complex system which involves human thinking. The CDISI fuzzy model is discussed in Section 3.

3. CDISI Fuzzy Model

A fuzzy system is developed on the basis of the fuzzy logic, which is based on the fuzzy set theory [9]. Fuzzy logic supports approximate reasoning by taking a broader view of Boolean values of 1 and 0 with fine merger of symbolic and numeric computation. All the input and output parameters in a fuzzy system are essentially fuzzy-subset [20] with each element having some degree of membership in the subset.

The CDISI fuzzy system model portrayed in Figure 3 consists of following elements.

(1) *Numerical Data Inputs.* The numerical values for all input parameters are extracted from the output waveforms generated with the help of data acquisition system. These numerical values for different parameters are used as inputs to CDISI fuzzy model. The numerical data inputs for CDISI system are input frequency, average RMS, standard deviation, location index, Arms, Amax, Brms, and Bmax.

(2) *Numerical and Linguistic Data Outputs.* The CDISI output waveform parameters lead to determine the nature of plate and the source of impact. The nature of plate $\in [0, 1]$ is also represented as *degree of crack*; the smaller the value of degree the less the amount of cracking. The linguistic labels applied to the output parameters are

(i) NatureOfPlate $\in$ {Unknown, Undamaged, Slightly Damaged, Damaged} $\in [0, 1]$,

(ii) SourceOfImpact $\in$ {SourceType1, SourceType2, SourceUnknown} $\in [0, 1]$.

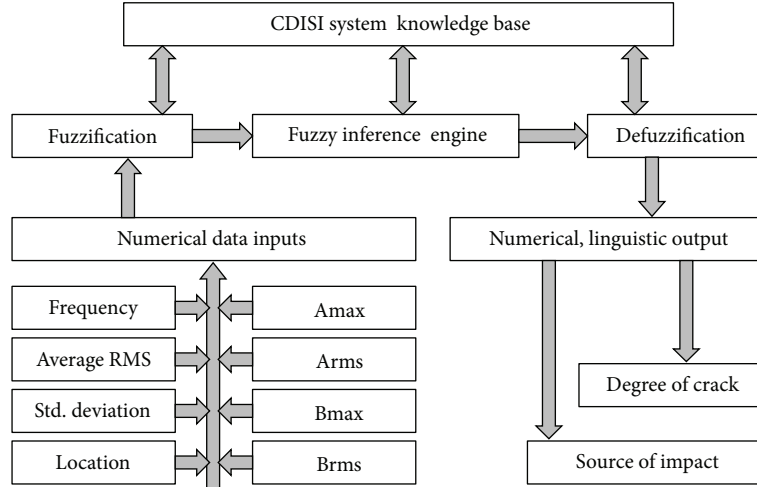Figure 3: CDISI fuzzy system model.

Table 1: Linguistic labels for the *index location* parameter.

Parameter	Labels		
	Near	Far	Faraway
Index location segments	Segments adjacent to sensor	Segments adjacent sidewise to the near section	Rest of the segments

(3) *Fuzzification.* It maps observed nonfuzzy input parameters into suitable linguistic values, which are defined as the labels of fuzzy parameter sets. The linguistic labels for input parameter location index can be seen in Table 1. The *near* label segments are shaded grey, *far* label segments are white, and *faraway* label segments are shaded in gradient in Figure 2. The linguistic labels for input parameters input frequency, average RMS, std. deviation, Arms, Amax, Brms, and Bmax can be illustrated in Table 2. The transformation of data into linguistic labels and vice versa is done with help of (1) and (2) and Table 3.

$$\text{Frequency}\,(x) = \begin{cases} \text{LL} & \text{if } 01 \le x < 30, \\ \text{LH} & \text{if } 30 \le x < 60, \\ \text{ML} & \text{if } 60 \le x < 70, \\ \text{MH} & \text{if } 70 \le x < 80, \\ \text{HL} & \text{if } 80 \le x < 90, \\ \text{HH} & \text{if } 90 \le x < 100, \\ \text{VH} & \text{if } > 110. \end{cases} \quad (1)$$

In (1) label is allocated to different values of the input frequency. These labels are further associated with membership functions from Table 3 equations for the different values of the linguistic labels used in the fuzzy model.

(4) *Fuzzy Inference Engine.* The major components of this block are

(a) a rule base: fuzzy rule can be expressed as

"*If input1 is A or input2 is B and input3 is C, then output is D,*" where A, B, and C are the input and D is output linguistic label values defined. With some experimentation, trialerror, past experience, and familiarity with the system that is to be developed the rules are formulated;

(b) fuzzy rule database: sets up the relation and defines the membership functions for each input and output parameter being used by the CDISI fuzzy rules;

(c) reasoning mechanism: this block generates the result by implementing the inference procedure on the given conditions and the formed rules. Different reasoning mechanisms can be used in a fuzzy system to obtain the desired result. The CDISI results are obtained by aggregating the result of each rule in the fuzzy rule base.

(5) *Defuzzification.* This component takes inputs as aggregated fuzzy dataset, the result of fuzzy inference engine and further maps it to a nonfuzzy output value for the *degree of crack/nature of plate* and *source of impact* outputs. The reverse process of the fuzzification is

$$\text{SourceOfImpact}\,(x)$$
$$= \begin{cases} \text{SrcType1} & \text{if } \text{trimf}\,(x, [-0.4, 0, 0.4]), \\ \text{SrcType2} & \text{if } \text{trimf}\,(x, [1, 0.5, 0.9]), \\ \text{SrcUnknown} & \text{if } \text{trimf}\,(x, [0.6, 1, 1.4]), \end{cases}$$

$$\text{NatureOfPlate}\,(x)$$
$$= \begin{cases} \text{UnKnown} & \text{if } \text{trimf}\,(x, [-0.3333, 0, 0.3333]) \\ \text{Undamaged} & \text{if } \text{trimf}\,(x, [0, 0.3333, 0.6667]) \\ \text{Slightly Damaged} & \text{if } \text{trimf}\,(x, [0.3333, 0.6667, 1]) \\ \text{Damaged} & \text{if } \text{trimf}\,(x, [0.6667, 1, 1.333]), \end{cases}$$

$$(2)$$

TABLE 2: Linguistic labels for the different parameters.

Labels	LL	LH	ML	MM	MH	HL	HH	VH
Range of value	Low-low	Low-high	Medium-low	Medium-medium	Medium-high	High-low	High-high	Very high

TABLE 3: Linguistic label membership function equations for different parameters.

Membership function equations
$LL(x) = \begin{cases} 0, & x \leq 0, \\ 0.1429 - x/0.1429, & x \in (0, 0.1429), \\ 0, & x \geq 0.1429. \end{cases}$
$LH(x) = \begin{cases} 0, & x \leq 0.1429 \\ x/(0.1429), & x \in (0, 0.1429), \\ 0.3 - x/0.1428, & x \in (0.1429, 0.2857), \\ 0, & x \geq 0.2857. \end{cases}$
$ML(x) = \begin{cases} 0, & x \leq 0.1429, \\ x - 0.1429/0.1428, & x \in (0.1429, 0.2857), \\ 0.2857 - x/0.1429, & x \in (0.2857, 0.4286), \\ 0, & x \geq 0.4286. \end{cases}$
$MM(x) = \begin{cases} 0, & x \leq 0.2857, \\ x - 0.2857/0.1429, & x \in (0.2857, 0.4286), \\ 0.4286 - x/0.1428, & x \in (0.4286, 0.5714), \\ 0, & x \geq 0.5714. \end{cases}$
$MH(x) = \begin{cases} 0, & x \leq 0.4286, \\ x - 0.4286/0.1428, & x \in (0.4286, 0.5714), \\ 0.5714 - x/0.1429, & x \in (0.5714, 0.7143), \\ 0, & x \geq 0.7143. \end{cases}$
$HL(x) = \begin{cases} 0, & x \leq 0.5714, \\ x - 0.5714/0.1429, & x \in (0.5714, 0.7143), \\ 0.7143 - x/0.1428, & x \in (0.7143, 0.8571), \\ 0, & x \geq 0.8571. \end{cases}$
$HH(x) = \begin{cases} 0, & x \leq 0.7143, \\ x - 0.7143/0.1428, & x \in (0.7143, 0.8571), \\ 0.857 - x/0.1429, & x \in (0.8571, 1), \\ 0, & x \geq 1. \end{cases}$
$VH(x) = \begin{cases} 0, & x \leq 0.8571, \\ x - 0.8571/0.1429, & x \in (0.8571, 1), \\ 0, & x \geq 1. \end{cases}$

where trimf(x, [a, b, c]) is the triangular function [21] with a, b, and c as left feet, right feet, and the peaks of triangle.

4. CDISI Fuzzy Inference System

Taking into consideration the automation of CDISI system for armor plates and the uncertainties pertaining to these kinds of systems, the fuzzy logic approach [12, 23] seems to be one of the promising candidates.

The CDISI Fuzzy Inference System is a multiple input multiple output (MIMO) system as shown in Figure 4. It has eight input and two output unique parameters. The Linguistic labels for the Index Location parameter are tabulated in Table 1 and rest of the input parameters in Table 2. The linguistic labels for the output parameters are expressed in (2). Table 4 shows the labels and range of values for different input parameters. The membership functions are assigned to each of these parameters. All of the CDISI parameter membership functions selected are triangular functions after some trial and error on experimenting with other membership functions like Gaussian, Trapezoidal, Gaussian bell and few more. It was observed that triangular function works well with the CDISI Fuzzy Inference System. Figure 5 shows the triangular membership function for the output parameters NatureOfPlate and SourceOfImpact. Figure 6 shows the triangular membership function for the input parameters like Average RMS and Location.

Table 5 shows a sample of the rule base, expressing the relationship between the input and output parameters. If any of the input parameter labels are *"true"* for a certain rule then that rule is said to be activated. About five dozen rules are incorporated in the CDISI System.

Fuzzy Logic Toolbox from MATLAB is used to build the CDISI fuzzy Inference System using Mamdani method [21]. The CDISI Fuzzy Inference System implementation snapshots can be seen in Figure 7. Figure 7(a) shows the MIMO structure of the CDISI Fuzzy Inference System. This portrays the input and the output parameters as discussed in Sections 2 and 3. A snapshot of CDISI Fuzzy System Rule Editor Window can be seen in Figure 7(b), which provides an environment to add, delete and update rules in the rule database.

5. FPGA Implementation of CDISI

CDISI system automation is done by rapid prototyping of a chip with the help of FPGA implementation [24–26]. The reference [1] has discussed the standalone device designed to detect cracks in armor plates. An effort is made to develop a chip which can detect crack and identify the source of impact on basis of logic used in the CDISI fuzzy inference system discussed in Section 4. FPGA implementation of the CDISI system is done using hardware description language Verilog with the Xilinx ISE WebPack [27], SynaptiCAD [28], and ModelSim XE [29] using Spartan 3 FPGA. CDISI FPGA implementation is a general-purpose, multi-level programmable logic device supported with advantages like

(1) flexibility to change rules on the hardware,

TABLE 4: Labels for the input function of CDISI fuzzy inference system.

Range				Labels				
	LL	LH	ML	MM	MH	HL	HH	VH
Arms	0.1–1.1	1.1–1.4	1.4–1.7	1.7–1.9	1.9–2.3	2.3–3.5	3.5–4	>4
Amax	0–6.5	6.5	6.5–8	8	8–10	10	10–17	>17
Brms	0–1.5	1.5–2.4	2.4–2.9	2.9	2.9–3.3	3.3	3.3–4.0	>4
Bmax	0–10	10	10–13	13	13–15.4	15.4	15.4–17	>17
Frequency (KHz)	1–30	30–60	60–70	70–80	80–90	90–100	100–110	>110
Avg. RMS voltage	0–0.001	0.001–0.00199	0.00199–0.00225	0.00225–0.00250	0.00250–0.002971	0.002971–0.003111	0.003111–0.004	>0.004
Standard deviation	≤0.00003	0.00003–0.00003229	0.00003229–0.00006229	0.00006229–0.0001	0.0001–0.0001889	0.0001889–0.000199	0.000199–0.00021	>0.00021

TABLE 5: Sample rule base for the CDISI fuzzy inference system.

| Rule no.	Freq	Avg. RMS	Std. dev.	Loc.	Arms	Amax	Brms	Bmax	Nature of plate	Impact source
1	MM	MM	MM	Far	HL	HH	LH	ML	Unknown	SourceType2
5	MM	MM	MM	Faraway	HL	HH	MH	ML	Unknown	SourceType1
18	MM	MM	MM	Near	VH	HH	ML	MH	Unknown	SourceType1
35	HH	LL	HH	Far	MM	MM	MM	MM	Damaged	SourceUnknown
42	HH	HH	MM	Far	MM	MM	MM	MM	Undamaged	SourceUnknown
54	MM	HH	LL	Far	MM	MM	MM	MM	Slightly damaged	SourceUnknown
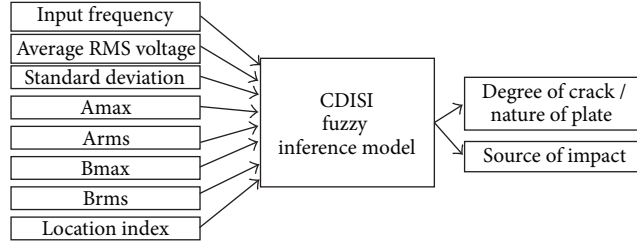
FIGURE 4: CDISI fuzzy inference system.
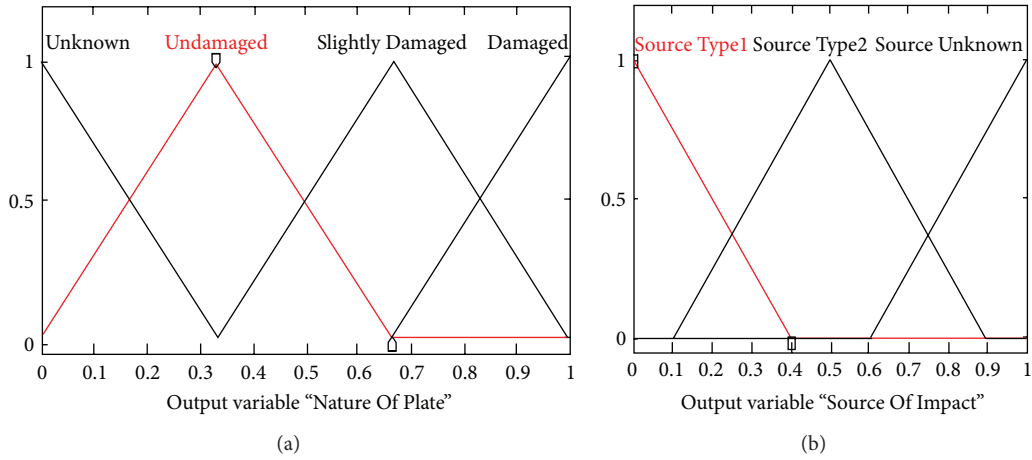

(a)

(b)

FIGURE 5: Output parameters membership function: (a) NatureOfPlate and (b) SourceOfImpact.
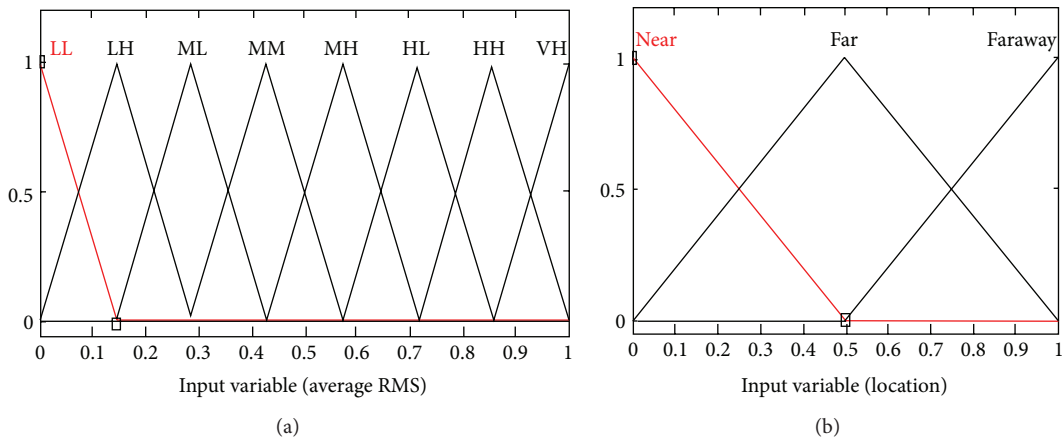

(a)

(b)

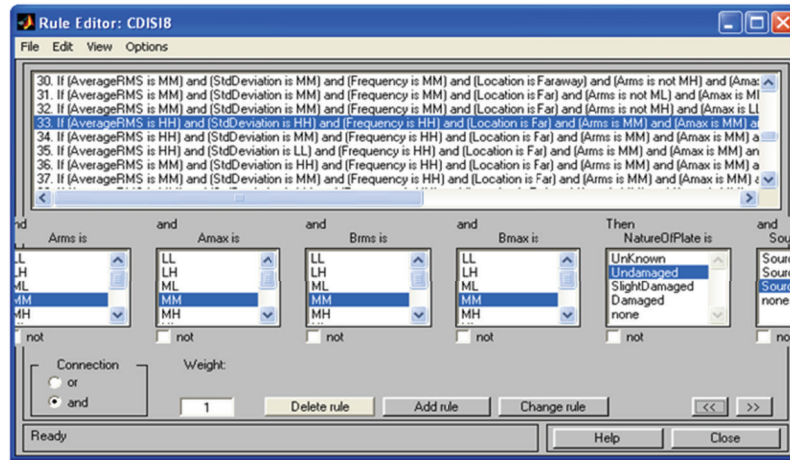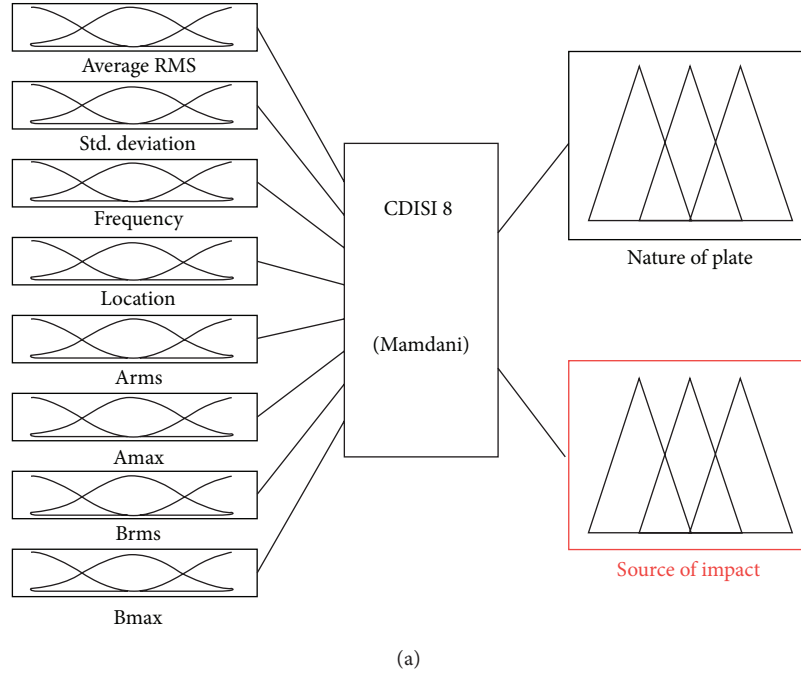FIGURE 6: Input parameters membership functions: (a) average RMS and (b) location.

(a)

(b)

FIGURE 7: CDISI fuzzy inference system: (a) the fuzzy inference system (FIS) and (b) the FIS rules.

(2) programing and reprograming using reasonably priced hardware and software on the field,

(3) cheaper option over the respective chip, with respect to the manufacturing cost and complexity of the chip.

Figures 8(a) and 8(b) show the structure of CDISI FPGA system and the RTL schematic, respectively. The system has the following 3-bit inputs: *Input Frequency, Average RMS, Standard Deviation, Amax, Arms, Bmax,* and *Brms.* The input *Location Index* is the only 2-bit input parameter. The output is restricted for the experimental purpose to 1-bit *ImpactSource* and 2-bit *Pltstatus* for source of impact and the nature of plate, respectively. The number of bits can be extended further to expand the input and the output domains. The status code bits, that represent the meaning associated with each numerical value result are tabulated in Table 6. They show the

value of output bus. For example, *Pltstatus* = 11 indicates that the plate is *damaged*, and *ImpactSource* = 1 indicates that the source of impact is *ImpactSource-Two.* Table 7 shows the CDISI FPGA implementation input status code bits for various 3-bit and 2-bit input parameters. This table has tabulated the possible input values that can be assigned to different input buses.

CDISI system technology schematic can be seen in Figure 9(a), which represents the design in terms of logic elements optimized to the target device. Figure 9(b) shows the detailed system register transfer level (RTL) schematic of the proposed CDISI system. RTL schematic view symbolizes design in terms of macro blocks. Each macro block has combinatorial logic mapping onto elementary logic function gates. Figure 10(a) shows the output HDL log of the software simulation using SynaptiCAD software of the CDISI system developed.
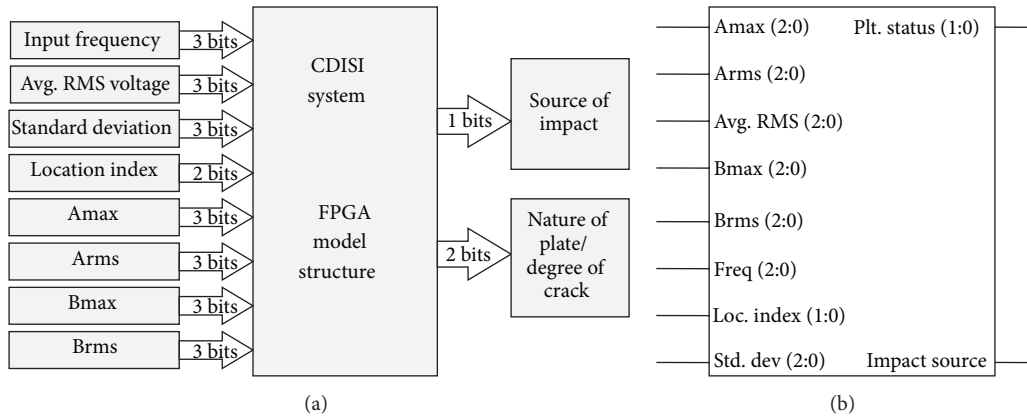
FIGURE 8: CDISI system FPGA implementation: (a) system design structure and (b) RTL schematic.
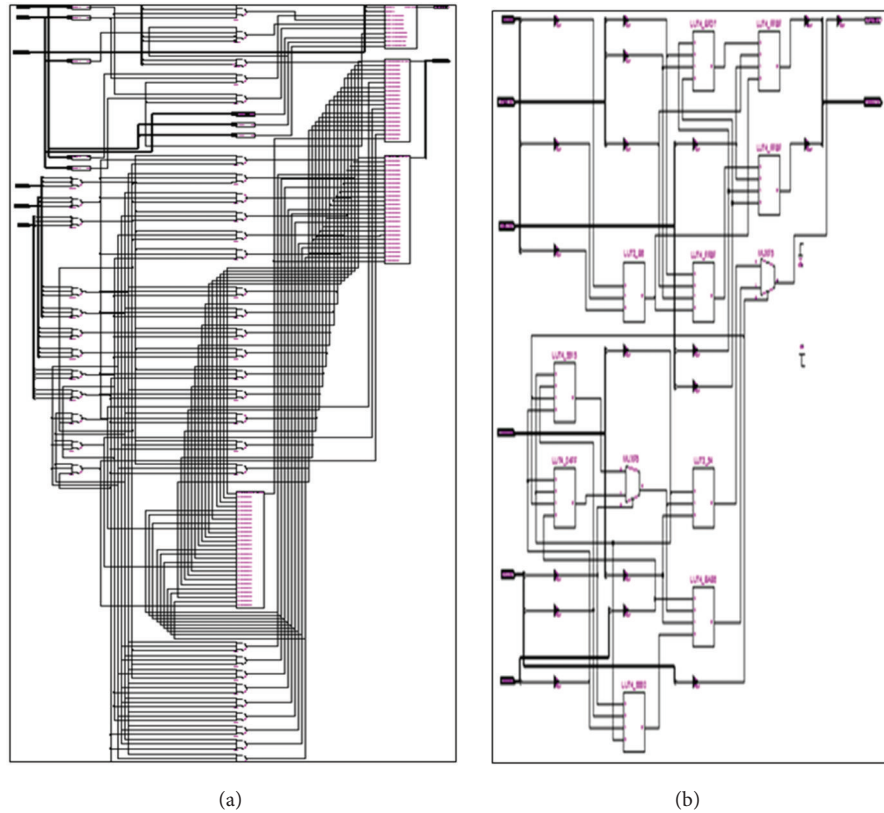

FIGURE 9: CDISI system: (a) technology schematic and (b) detailed RTL schematic.

Some sample results can be observed here in Figure 10(a) for a set of input parameters. Figure 10(b) shows the waveform simulation for the CDISI system. Table 8 shows the analysis of CDISI system implementation device usage. It can be seen in Table 8 that LUT (Lookup Table) utilization is 1%. Slice, an elementary programmable logic block which includes two 4-input LUTs, two multiplexers, arithmetic logic unit, and two 1-bit registers, has the utilization of 1%. Thus Table 8 illustrates minimal device usage by the CDISI system.

6. CDISI System: An Integrated Approach

CDISI System supports an automated and integrated approach towards crack detection and the impact source identification in ceramic plates. This integrated approach consists of CDISI fuzzy inference system and the CDISI field-programmable gate array (FPGA) implementation as shown in Figure 11. The test circuit discussed in Section 2 generates waveforms which can be displayed on an oscilloscope. The test circuit results are further used to extract the data which

Table 6: CDISI FPGA implementation output status code bits.

CDISI output	Nature of Plate status (2-bit)				Source of Impact (1-bit)	
	Unknown	Undamaged	Slightly damaged	Damaged	ImpactSource-One	ImpactSource-Two
Output bus code	00	01	10	11	0	1
Numerical value	0	1	2	3	0	1

Table 7: CDISI FPGA implementation input status code bits.

Input labels	3-bit input parameters								2-bit input parameters		
	LL	LH	ML	MM	MH	HL	HH	VH	Near	Far	Faraway
Range of value	Low-low	Low-high	Medium-low	Medium-medium	Medium-high	High-low	High-high	Very-high	low	medium	high
Input bus code	000	001	010	011	100	101	110	111	00	01	11
Numerical value	0	1	2	3	4	5	6	7	0	1	3

Table 8: Analysis of FPGA implementation of CDISI.

Metric	Used	Available	Utilization
Number of 4 input LUTs	10	3,840	1%
Number of Slices occupied	6	1,920	1%
Additional JTAG gate count for IOBs	912	—	—
Number of bonded IOBs:	19	173	10%
Total equivalent gate count for design	66	—	—

proceed as input for the CDISI System. The CDISI fuzzy inference system generates the result {Pltstatus, ImpactSource}. CDISI field-programmable gate array (FPGA) implementation utilizes and implements the rule base from fuzzy inference system.

The proposed algorithm for an integrated approach towards CDISI consists of following subsystems.

(1) CDISI system test circuit parameter extraction: extracts the parameters from the results generated by the circuits discussed in Section 2 with the help of DEWESoft Data acquisition system.

(2) CDISI fuzzy inference system: develops CDISI fuzzy inference system which essentially is a multiple-input, multiple-output fuzzy system, based on the behavior extracted from the data.

(3) CDISI field-programmable gate array (FPGA) implementation: identifies the inputs and outputs for the CDISI chip, develops Verilog code for CDISI in ceramic plates on Spartan 3 FPGA, and writes a test-bench file to simulate and verify the FPGA implementation.

(4) Display output: nature of plate (Pltstatus) and source of impact (ImpactSource) are the two outputs displayed by both the fuzzy and the FPGA implementations.

The detailed proposed algorithm for overall development of CDISI system which consists of the fuzzy inference and FPGA implementation consists of the following steps.

(1) Acquire sensors A and B waveforms using DEWESoft 7 data acquisition system (DAS) and save them in two data files.

(2) Extract the input parameters from the waveform data obtained by the test circuit discussed in Section 2.

(3) Identify the input and output parameters for CDISI fuzzy inference system as seen in Figures 1 and 2.

(4) Set the range for the input and output parameters. CDISI parameter range is tabulated in Table 4.

(5) Define CDISI fuzzy model [6, 17] using Mamdani type fuzzy inference system, considering absolute values of parameters.

(6) Fuzzify the input parameters and map an observed nonfuzzy input space into suitable linguistic values as seen in Tables 1 and 2.

(7) Define membership function for each input and output parameter with experimentation.

(8) Develop fuzzy rule base on the basis of data collected.

(9) The result is obtained by aggregating the result of each rule in the fuzzy rule base for the considered input.

(10) Defuzzify the output and map it to nonfuzzy linguistic output values (Nature of Plate) and (SourceOfImpact).

(11) Identify number of bits required to represent the CDISI system input and output parameters on a chip as identified for the fuzzy system and determine the dimension of the system structure as observed in Figure 8.

(12) Develop Verilog hardware description language code for CDISI system for ceramic plates.

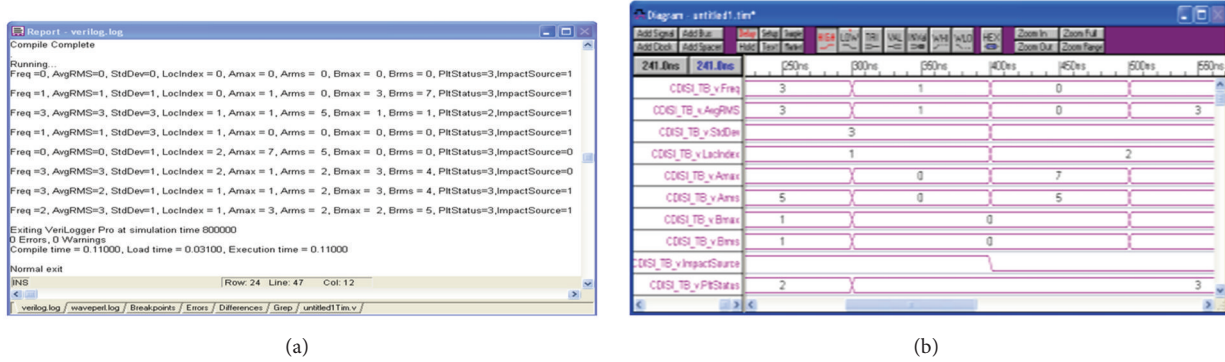(13) Select device as FPGA and assign package pins for CDISI design on FPGA.

(a)   (b)

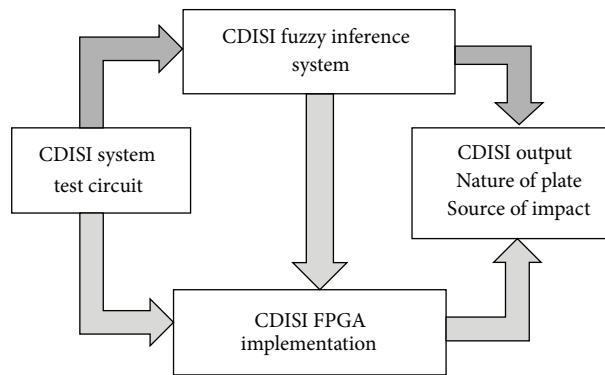FIGURE 10: CDISI simulation: (a) HDL log and (b) waveform simulation.

FIGURE 11: An integrated approach towards CDISI.

(14) Generate a netlist PROM file to be downloaded on the Spartan 3 FPGA.

(15) Configure the FPGA and program FPGA; verify the design using input output signal pins/buttons on FPGA.

(16) Write a Verilog test-bench file for software simulation and verification of the FPGA implementation.

(17) Run the test bench file with help of any of the tools like SynaptiCAD Verilogger Pro and ModelSim.

7. Conclusion

The problem of crack detection has aroused interest amongst a large number of investigators because of its importance in a variety of applications. Similarly there has been interest in identifying the source which is responsible for making the crack. In this paper a unified approach for crack detection and the impact source identification is proposed. Because of the importance of the problem it is essential to develop the chip which can have the algorithm for CDISI problem implemented. It is revealed in this paper that the concept of fuzzy logic and the rule base developed by the fuzzy logic can be implemented to solve this problem in industry. The fuzzy rule base can be developed in the form of a Verilog code, which further enables the field-programmable gate array (FPGA) implementation of the suggested technique. The

suggested technique is implemented using Xilinx's Spartan 3 FPGA and ISE WebPACK 9.1i software. The software simulation and debugging is done by means of SynaptiCAD's Verilog Simulator—VeriLogger pro—and ModelSim. The proposed FPGA implementation reads the values of input parameters and exhibits the nature of plate and source of impact. The entire algorithm has been successfully implemented for integrated crack detection and impact source identification and can possibly act as a hand held device for the detection of crack and to identify the source of impact. The current CDISI system can be expanded by inclusion of more parameters and extended range for the parameters. The suggested procedure can show the way to the solutions for several other similar problems of interest in the industry.

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