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Evaluation and Prediction of Self-healing Assessments for AA2014 Based Hybrid Smart Composite Structures: A Novel Fuzzy Logic Approach

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A B S T R A C T

An idea to heal the damaged surface through healing agents in metallic composite are at their developmental stage. Therefore, the selection of design parameters for a new generation smart composite is more complex and difficult. In the present study the two case studies on self healing smart strucures are included with different input design parameters to evaluate the healing properties. Taguchi based L-8 experiments were conducted to analyze the influencial parameters responsible for higher self healing assessments (i.e. recovery in crack width, recovery in crack depth and flexural strength recovery). To evaluate the self-healing assessments of the damaged structure, a soft computing technique based on S/N ratio from ANOVA analysis is obtained. The experimental results were further considered for constructing the fuzzy logic predictive model. Linear regression models i.e. a statistical tool is generated to judge the accuracy of the fuzzy based predicted model through various error analyses. Based on S/N ratio Fuzzy logic model, results show less error values of 6.33 and 4.94 % for case studies I and II, respectively in compared to the regression model adapted for all self-healing assessments. The model offers a close resemblance with the experimental observations even with less number of experimental runs. This concludes that the fuzzy logic model provides a powerful soft computing tool to perform large research work related to the design of input parameters for metallic based self-healing composites structures in near future.

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1. INTRODUCTION

Metals are always serving the development and advancement of civilization since the prehistoric ages. The diverse phase for the discovery of metals and their processes has been evolved according to the need and usage of mankind. A long journey of monolithic metals towards alloys to the different classes of composites has been globally accepted for their commercialized products and assets [1]. For centuries, nature is always an inspiration to mankind. Biomimetic is defined as applying the mechanism of biological species to employ in the engineering technology. The material which has an ability to self-sustain and recuperate itself with the resources available to it is called self-healing material [2]. The smart structure can be categorized depending upon the nature of healing i.e. intrinsic and extrinsic healing. The extrinsic healing approach has been adapted for higher melting point processed metals as a healing agent is stored in hollow fibre or tubes, microvascular networks etc. and reinforced in the matrix [3-6]. The damage control that occurs without the intervention of human effort comes under the category of passive modes. Whereas, the damage control that occurs with the intervention of human effort is termed as active mode. This emerges an interdisciplinary field both at macro and micro scale to explore the features of the mechanism in materials, electronic devices, structures etc. [7-8]. With the advancement in technologies and depletion of natural resources, researchers are bound to focus their research towards sustainable development. A global report shows that CO_2 emissions had been globally hit to a 2.7%

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increase in 2018 compared to 1.6% in the year 2017. United Nations environment programme reports that with expanding population, natural resources are expected to grow by 110 %, leading to reduced forest reduction by 10% and reduction in habitat to 20% by 2050. Implementing the self-healing phenomenon in metallic structures leads to the minimization of replacement of old components with new ones and serviceability of damaged components in remote conditions can be made more effective [9]. One of the successful cited examples of self-healing is the Nissan Company has successfully launched the clear coat hydrophobic paint "Scratch guard coat" that repairs the scratch depending upon the surrounding temperature and condition within 1 to 7 days of damage [10]. Similarly, Ionomers poly Ethylene-co-methacrylic acid has found its applications in self-repair windows and shooting targets under ballistics self-repair phenomenon [11]. Chromate based pigment (BaCrO4 or SrCrO4) introduced with epoxy polyamide matrix act as self-sealing coatings for corrosion protection. Bacteria based crack healing on degraded limestone; ornamental stone and concrete surface has been comprehensively reported during the research at Delft University [12]. Reinforcing agents are an essential source that provides the strength and healing nature of the composites [13-14]. Therefore before selecting the healing agent, it should fulfil certain criteria that are as follows:

1. The reinforcing agent should have sufficient high yield strength greater than that of the matrix.
2. The activation temperature of healing agents should fall within the conditions of the final healing temperature.
3. The healing agents should have high adhesive bonding (i.e. wetting property) with the parent matrix.
4. The healing agents should have high adhesive bonding (i.e. wetting property) with the parent matrix.
5. The healing agents should not lose their healing properties and dimensional stability even at high temperatures.
6. The reinforcing agents should respond to any external source (i.e. heat, light) to start the healing procedure.
7. The healing agents do not increase the overall weight of the composites' structure.

The right execution of smart material design may result in a viable solution for sustaining the structure's integrity and longevity even in difficult situations [15]. The design and fabrication of smart composites is a costly affair. Therefore there is a need of predictive model to evaluate the results more efficiently. Nowadays, a technique can be incorporated for optimal design selection process in order to identify new material selection approaches that cover more environmental considerations and time utilization and saving [16-17]. Fuzzy set theory was created to cope with these types of decision-making challenges and to arrive at a reasonable solutions for them in a timely manner [18]. An overall idea for successfully implementation for the design of smart materials is shown Figure 1.

To uncover the healing mechanism in metallic composites, parameters influencing the design of the self-healing composite structure for effective recovery in healing assessment are analyzed using orthogonal array L8 Taguchi techniques. A comparative analysis was done based on Taguchi analysis on all different smart structure fabricated namely AA2014-NiTi strip-solder based metallic composites and AA2014-NiTi wire-solder based metallic composites. The healing response is measured by considering maximum recovery in the healing assessment for all two different cases. The input parameter's individual contribution is also determined using S/N ratio of every healing assessment and for every experimental run during analysis. Further MATLAB based Fuzzy logic predictive model was developed to predict and compare the self-healing assessment for various fabricated self-healing composite structures.

This paper is organized as follows: Section 2 defines the material composition and a short description of fabricated composite, Section 3 comprises of testing setup for evaluating the self-healing assessments analysis. Section 4 includes design methodology, predictive models and error analysis involved in the present study. Section 5 includes the description and formulation of fuzzy model for both the case study i.e. (Self-healing assessments for AA2014-NiTi strip-solder alloy based hybrid metallic composites) and (Self-healing assessments for AA2014-NiTi strip-solder alloy based hybrid metallic composites) included in the study. The results obtained from the fuzzy based predictive rule and regression model is compared along with confirmatory test using different error analysis is discussed in section 6. Finally, the summarized results were described in conclusion section 7 followed by the references.

2. EXPERIMENTAL DETAILS FOR THE ANALYSIS OF SELF-HEALING COMPOSITES

The composites were fabricated via casting method. An ingot of AA2014 alloy was melted in an electric furnace at 750 ºC and poured directly into the customized die that already containing shape memory alloy (SMA) wire/strip inside it. Once casted and solidified the casted composite were filled with solder alloy and sealed with refractory cement to avoid draining of solder during heat treatment [19-22].

2. 1. Materials The functional biomimetic composite structure includes SMA's strip and low

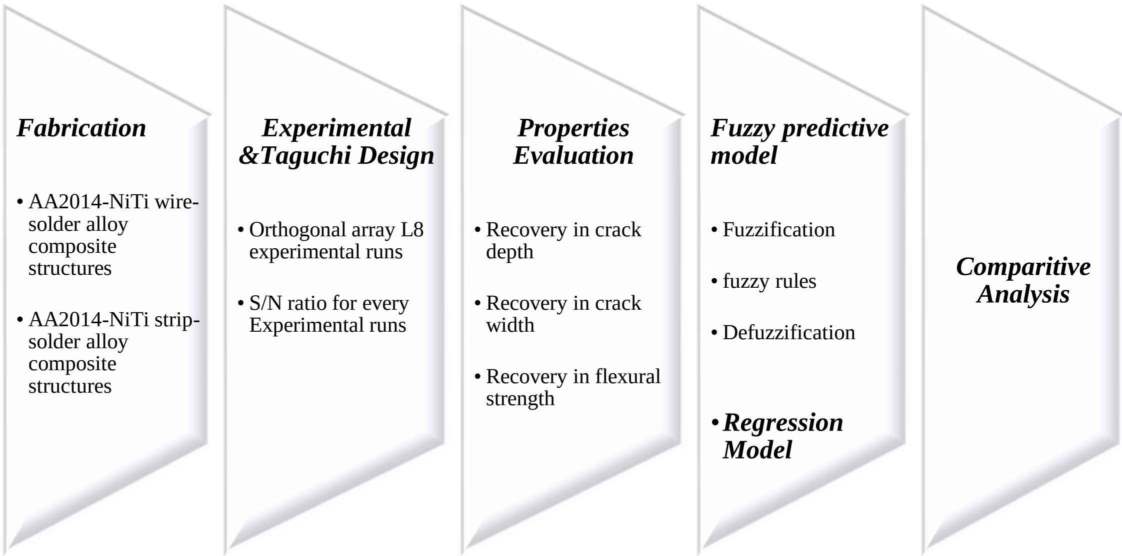


Figure 1. An overall procedure involved in conducting the analysis

melting alloy (Sn-Pb) as internal combination parameters reinforced in aluminium alloy-based matrix during fabrication. The purpose for introducing two healing agents was to revert the damage structure to its original state and simultaneously bind the micro crack interfaces.

2. 1. 1. Self-healing Composites Matrix Details An aluminium alloy AA2014 is used as a matrix which has been reinforced with different healing agent to form a hybrid MMC's. The transition temperature of the phase transformation (i.e. Martensite to Austenite phase) for SMA strip is 70 ºC, whereas, the melting point of solder alloy is 181 ºC. The chemical composition of AA2014 matrix confirmed through Energy Dispersion X-Ray (EDX) technique as summarized in Table 1 [19-22]

2. 1. 2. Healing Agents

2. 1. 2. 1. Ni-Ti alloy Owing to its advantages over other SMA groups, Ni45Ti55-based SMA was mostly employed as reinforcement, because of its transformation hysteresis, which aids in repeating actuation with a shorter time interval [22-23]. The nitinol wires with a diameter of 0.46 mm and nitinol strip of 0.98 mm having a final austenite temperature of 70°C was used as reinforced healing agents for case studies I and II, respectively. Nitinol is a frequently used and commercially accessible SMA and in the present study both forms (i.e. wire and strip) were acquired from SMA wires India Ltd. It offers great corrosion resistance, biocompatibility, high damping capability, and performs in low cycle fatique [20].

TABLE 1. Chemical composition of AA2014 used as a matrix [19-22]

Element	Al	Cu	Si	Mg	Mn
Wt. (%)	93.7	4.4	0.8	0.4	0.7

2. 1. 2. 2. Solder Alloy The most popular and commercially available is Sn60Pb40 based solder alloy with applications in electronics industries for the joining of copper wires and circuit boards. With an increase in Sn%, the solder alloy (i.e. Sn63Pb37) with a eutectic composition has more resistant to oxide formation with large shear and tensile strength. Although the commercialized solder alloy Sn60Pb40 has a low melting point of 180 ºC having a high wetting property, low oxide content, large flow ability that bonds the damaged crack through the phenomenon of capillary action and surface tension. The properties of solder alloy using in the analysis are stated in Table 2 [19-20].

TABLE 2. Chemical composition of solder alloy used as a healing agent [19-20]

Solder alloy	Melting Point (ºC)	Density (g/cm^3)	Electrical Resistivity (μΩ-m)	Thermal Conductivity (W/m-K)	Tensile strength (MPa)	Tensile Elongation (%)	Brinell Hardness (HB)
Sn60Pb40	183/191	8.51	0.155	50	52.46	41	17

2. 2. Composites Structures

2. 2. 1. AA2014-Niti Strip Solder Based Hybrid Metallic Composite Structure A hybrid metallic smart composite consists of nitinol strip at the center that extends longitudinally placed throughout the sample. The solder alloy is located at the middle of the strip both top and bottom throughout the length of the sample. AA2014-NiTi strip-solder alloy based hybrid metallic composites is shown in Figure 2.

2. 2. 2. AA2014-Ni-Ti Wire-solder Based Hybrid Metallic Composite Structure The structure consists of AA2014 as a matrix that contains solder alloy and Ni-Ti wires as a healing materials. The Ni-Ti wire extends longitudinally throughout the length of the composites, whereas solder alloy is located at the center of the composite material. After initial damage in the structure the healing agents activates by heating the damaged specimen and heals the crack developed in the structure. The fabricated composite is shown in Figure 3. A detailed fabrication setup for the self-healing composite is discussed in the literature [19].

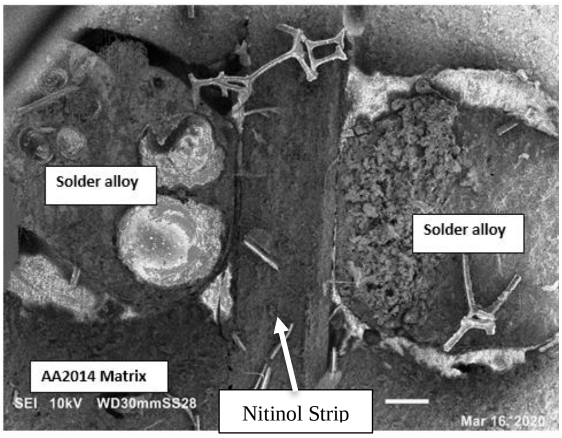


Figure 2. SEM micrograph of the fabricated hybrid composite

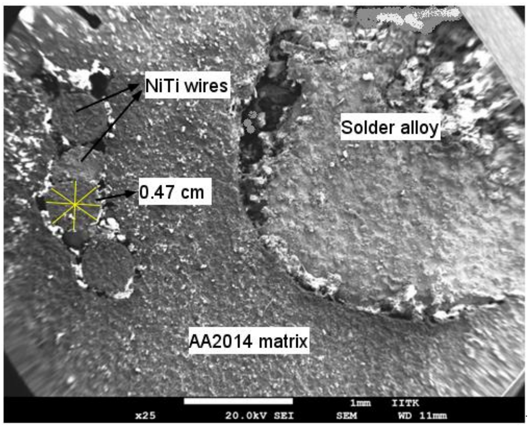


Figure 3. SEM micrograph of fabricated hybrid composite

3. TESTING SETUP

3. 1. 1. Crack Width Analysis The crack width were examined using optical microscope before and after healing. The analysis of crack width measurement were considered at the same and exact position before and after healing to maintain the uniformity in measurement [19-22]. Therefore, the recovery in crack width was evaluated. The crack width recovery %. is calculated using expression given in Equation (1) [13].

$$\eta_{reduction\ in\ crack\ width/crack\ depth} = \frac{\alpha_{before\ healing}-\beta_{after\ healing}}{\alpha_{before\ healing}} \quad (1)$$

where, **"α"** is the property of interest i.e. crack width or crack depth

3. 1. 2. Crack Depth Analysis The surface crack depth is difficult to quantify as surface crack is ranged in micrometer. Therefore, highly sensitive Nondestructive testing i.e. eddy current test was conducted at different frequencies [24]. A calibrated approach was opted to obtain the regression equation at different frequencies by calibrating the slots (created by EDM) of different depth of same nonferrous material to find the crack depth of actual samples. The electromagnetic signal received after calibration at different frequencies helps to formulate the regression equation using Equations (2) and (3) below [19, 21-22].

$$d = av + b\phi + c \quad (2)$$

where, d= Crack depth,

v = electromagnetic voltage,

$\emptyset$ = Phase angle,

a, b, c= arbitrary constant

$$\begin{aligned} &For\ Frequency\ 25\ kHz: d_{25} = 2.3255v + 0.00232\phi - 0.3790 \\ &For\ Frequency\ 50\ kHz: d_{50} = 3.9285v - 0.03571\phi + 6.5285 \\ &For\ Frequency\ 100kHz: d_{100} = 3.2456v - 0.01403\phi + 2.4763 \\ &For\ Frequency\ 200kHz: d_{200} = 4.0566v - 0.0169\phi + 2.9564 \end{aligned} \quad (3)$$

3. 2. 3. Flexural Test Initially the samples were bend tested at yield point to produce a damage to the composite structure. Thereby after healing the samples at 600ºC the samples were undergone re-bending test to evaluate their recovery in flexural strength. The three point bend was performed on Universal Testing Machine (Tenius Olsen load capacity 10 KN) at constant strain rate of 0.0166/s [19-22]. The expression for calculating the flexural stress and strain is given in Equation (4). The strength recovery % is obtained using expression in Equation (5) [14].

$$\sigma_{flexural\ stress} = \frac{3Fl}{2bt^2} \tag{4}$$

where, F = Flexural Load; l = Specimen length; b = Specimen breadth; t = Specimen thickness

$$\eta_{healing\ efficiency} = \frac{\alpha_{healed\ sample}}{\alpha_{damaged\ sample}} * 100 \tag{5}$$

where, **"α"** is the property of interest i.e. Flexural strength

4. DESIGN METHODOLOGY

4. 1. Taguchi Design of Experiment

Taguchi's orthogonal array employs a significant portion of these choices, taking use of the features of fractional factorial design to choose the optimum process parameter combination. The design of experiments performed using L8 orthogonal array Taguchi technique was analyzed using Analysis of variance (ANOVA) based S/N ratios to observe the most influential parameters affecting the design and performance of self-healing assessments [14, 16]. The relation to find the S/N ratio for larger is better is calculated using Equation (6). Using Taguchi orthogonal columns of L8 (4^1 2^3) array technique different experimental run for different fabricated smart structures was carried out.

$$\frac{S}{N} = -10log\left(\sum\left(\frac{1}{Y^2}\right)/n\right) \tag{6}$$

where, Y = responses for the given factor level combination and

n = number of responses in the factor level combination.

The normalized S/N ratio is evaluated using the relation given below in Equation (7)

$$N_i = \frac{x_i}{\sum_{i=1}^{i=n} x_i} \tag{7}$$

The proposed methodology provides a regression correlations based on the linear fit obtained using the following experimental data as stated in Equation (8) [25].

$$U = a_0 + P1a_1 + P2a_2 + P3a_3 + P4a_4 \tag{8}$$

where, $U = Output\ response,$

$a_0 = Constant\ intercept\ at\ y\ axis,$

$a_1, a_2, a_3, a_4 = Coefficient\ of\ Regression\ equation\ ,$

$P1, P2, P3, P4\ are\ the\ input\ parameter\ for\ the\ design\ of\ composites$

Linear regression models i.e. a statistical tool is generated to judge the accuracy of the predicted model. The model is generated using Minitab 19. The quality measures are adopted to compare and measure the model using error analysis [18]. To compare anticipated and measured results of self-healing evaluations, statistical measures such as the root mean square error (RMSE) and the determination coefficient (R^2) are employed. The RSME is defined using expression in Equations (9) and (10) [26].

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{pred\ i} - y_{observ} i)^2} \tag{9}$$

whereas, R^2 can be found using an expression below

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{pred\ i} - y_{observ\ i})^2}{\sum_{i=1}^{n} y_{observ\ i}{}^2} \tag{10}$$

The mean of the squares of the errors is assessed by the mean absolute percentage error (MAPE). MAPE values that are lower ensure that the suggested models perform better. The MAPE is computed using Equation (11) [27].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_{pred\ i} - y_{observ\ i}|}{y_{pred\ i}} * 100\% \tag{11}$$

Furthermore, the suggested models' effectiveness and efficiency are also evaluated using mean absolute error (MAE) that is determined by Equation (12) [28-30].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_{pred\ i} - y_{obser\ i}| \tag{12}$$

where n is the number of data patterns in the data set, $y_{pred\ i}$ indicates the predicted value of one data point i and $y_{observ\ i}$ is the observed value of one data point i.

4. 2. Fuzzy Predictive Model

According to this theory, it states, "If in an environment of discourse A, where $\hat{F}$ being a fuzzy subset of say X, can be specified by a membership function $f_f(a)$, which drafts each and every element "a" in A to a real number N within the interval [0, 1]. The function value $f_{\hat{F}}$(a) represents the grade of membership of "a" in $\hat{F}$. Larger the value of $f_{\hat{F}}$(a) stronger will be the grade of membership for "a" in $\hat{F}$ ". Fuzzy Logic is a multi-valued logic that provides the assessment of a collection of variables by establishing intermediate values between traditional evaluation schemes such as true/false, yes/no, high/low, and so on. In this approach, assessment concepts such as fairly tall or extremely quick may be mathematically expressed and analyzed by computers, allowing the software to use a more human-like style of thinking [31-32]. The event and kind of membership function are mostly determined by the relevant event when selecting membership functions for fuzzyfication [33-34]. The relationships between input parameters and output response were referred to construct the rules between them. On the basis of Mamdani fuzzy logic, the experimental data findings were simulated in the MATLAB programme. Parameters {a b c} define the triangular shaped membership function for input is shown in Equation (13) [34].

$$triangle\ (x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \geq b \\ \frac{c-x}{c-b}, & b \leq x \geq c \\ 0, & c \leq x \end{cases} \quad (13)$$

where a, b, c defines the x coordinates of the three corners of the underlying triangle membership function, generated by the triangular fuzzy triplet. De-fuzzification is the process of converting a fuzzy quantity to a precise value, whereas fuzzyfication is the process of converting a precise value to a fuzzy number. The model selection is critical since it determines the model's accuracy [35-36]. The centroid of area (COA) De-fuzzification approach is employed in this model because it provides extremely accurate prediction and analysis, as shown in Equation (14) [37]. An overall fuzzy inference system is shown in Figure 4.

$$COA = \frac{\int_{x_{min}}^{x_{max}} f(x)x dx}{\int_{x_{min}}^{x_{max}} f(x) dx} \quad (14)$$

where, $COA = Center\ of\ Area, x = value\ of\ linguistic\ variable$
$x_{max}\ and\ x_{min}\ is\ the\ range\ of\ the\ linguistic\ variable.$

The knowledge base is generally referred as a combination of rule base and database. In most cases, a fuzzy IF THEN rule has two aspects. The first portion, IF, and the second, THEN, are referred to as the premise and consequence, respectively [38-40]. A fuzzy rule base is comprised of a series of if-then control rules that have been created to illustrate the inference link between the input parametric design and the output self-healing evaluations. It is represented as shown below.

Rule 1: If $x_1 = a_1, x_2 = b_1, x_3 = c_1\ and\ x_4 = d_1$ then healing assessment is e_1
Rule 2: If $x_1 = a_2, x_2 = b_2, x_3 = c_2\ and\ x_4 = d_2$ then healing assessment is e_2
Rule 3: If $x_1 = a_3, x_2 = b_3, x_3 = c_3\ and\ x_4 = d_3$ then healing assessment is e_3
Rule n: If $x_1 = a_n, x_2 = b_n, x_3 = c_n\ and\ x_4 = d_n$ then healing assessment is e_n
Where, a_i, b_i, c_i and d_i are the fuzzy subsets which are being defined by a membership functions and e_i healing assessment output.

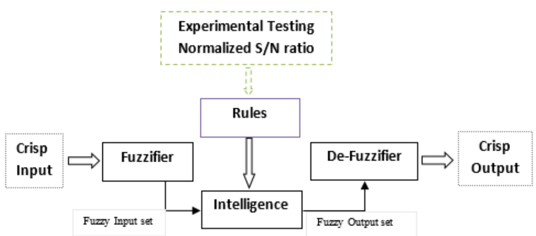


Figure 4. A flowchart rule based fuzzy inference system

5. VERIFICATION OF THE PROPOSED FUZZY MODEL FOR PREDICTION OF SELF-HEALING ASSESSMENTS

The proposed fuzzy model is designed with a view to accurately predict the self-healing assessment (i.e. Crack width recovery %, Crack depth recovery % and flexural strength %), respectively. The design consideration for the fabrication of smart composites is to achieve higher self-healing assessments. Therefore, based on knowledge and expertise of designer this predictive rule based model provides a tool for choosing an optimal input parameters for achieving the higher healing assessments. For evaluating the performance three cases were studied: (i) to predict Self-healing assessments for AA2014-NiTi strip-solder alloy based hybrid metallic composites. (ii) to predict Self-healing assessments for AA2014-NiTi wire-solder alloy based hybrid metallic composites.

5. 1. Case Study-I: To Predict Self-healing Assessments For AA2014-Niti Strip-Solder Alloy Based Hybrid Metallic Composites

The concept of the smart composites was made such that the reinforced SMA strip recovers the deflected damaged shape caused due to loading which ultimately heals the macro crack. Solder alloy heals the micro cracks by bonding the damaged site. A parametric study of AA2014 matrix considering different levels of input parameters (healing duration, SMA vol.%, solder alloy %, Reheat treatment) as reinforcement were studied using Taguchi L8 (Mixed level design) orthogonal array technique to determine the influential parameter affecting the self-healing assessments. The parameters and their levels considered for fabrication with different experimental runs is shown below in Table 3.

Initially, based on L8 mixed orthogonal array and based on the different combination of parameters, the experiments were carried out to evaluate the self-healing properties. The evaluated S/N ratio from Equation (6) for each experimental runs is utilized for deciding the range of output membership functions as shown in Table 4. Since the value for S/N ratio for each experimental run is unsystematic (i.e. negative); therefore, the values were normalized between 0 and 1. This will assists in deciding the range of output membership functions. In the later

TABLE 3. Input parameters selection with their considered levels

Parameters	Level 1	Level 2	Level 3	Level 4
Healing Duration (In min.)	30	60	90	120
Solder alloy vol. %	9	16	-	-
SMA strip vol. %.	10	13	-	-
Reheat treatment	Done (1)	Not Done (0)	-	-

TABLE 4. A summarized Table show the L8 orthogonal array experimental runs along with obtained healing assessments

Healing Duration.	Solder alloy vol. %	SMA strip vol. %.	Reheat Treatment.	Crack width Recovery %	S/N ratio	Normalized S/N ratio	Crack depth recover %	S/N ratio	Strength recover %	S/N ratio	Normalized S/N ratio
30	9	10	1	78.26	-2.12	0.114	37.89	31.57	35.94	-8.88	0.15
30	16	13	0	64.28	-3.83	0.207	22.21	26.93	15.76	-16.04	0.27
60	9	10	0	68.23	-3.32	0.179	50.89	34.13	36.2	-8.82	0.15
60	16	13	1	74.22	-2.58	0.139	53.95	34.63	45.4	-6.85	0.12
90	9	13	1	80.62	-1.87	0.100	54.87	34.78	55.96	-5.04	0.08
90	16	10	0	78.98	-2.05	0.110	78.45	37.89	64.08	-3.86	0.06
120	9	13	0	73.01	-2.73	0.147	60.06	35.57	56	-5.03	0.08
120	16	10	1	100	0	0	87.85	38.87	75.4	-3.01	0.05

stage during evolution for the recovery in healing properties, the normalized S/N ratio is converted into actual S/N ratio to acquire actual healing assessments for each experimental run.

An overall formulation of Mamdani based fuzzy interference system for predicting the self-healing assessment is shown in Figure 5. The next step includes the assessment and configuration of input membership design properties function to present in the linguistic variables. The crisp values of design parameters namely Healing duration, solder alloy vol. %, SMA vol. %, and reheat treatment factor are fuzzified as shown in Figure 6. For instance, the fuzzy set value for healing duration as input design parameters are classified as "Low", "Medium", "high", "Very high".

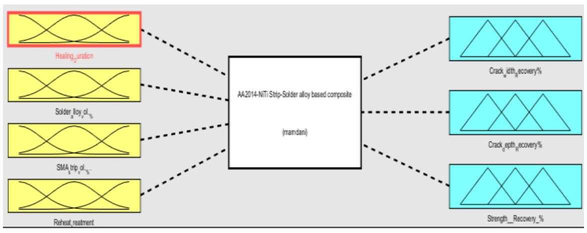


Figure 5. An overall Mamdani based fuzzy interference system for case study I

The S/N ratio of the heling assessment is considered as the actual response of output membership functions. The crisp values output response is fuzzified into linguistic domain. For instance, crack width recovery % is classified as "Very High", "High", "Medium", "Low" and "Very Low" respectively as shown in Figure 7. The formulation of knowledge based rule between input and output membership function provides an inference relationship between parametric combinations of experimental trails. This provides a wider scope and range of application in compared to other statistical methods. By studying the data set as shown in Table 4 fuzzy set data classified in the linguistics variable is used by the expert to create the set of rule between input and output membership functions as shown in Table 5.

5. 2. Case Study-II: To Predict Self-Healing Assessments For AA2014-Niti Wires-Solder Alloy Based Hybrid Metallic Composites

Flexural testing has been used to evaluate the healing evaluation of the AA2014 matrix reinforced with Ni-Ti wires and solder alloy as healing agents. The concept behind a

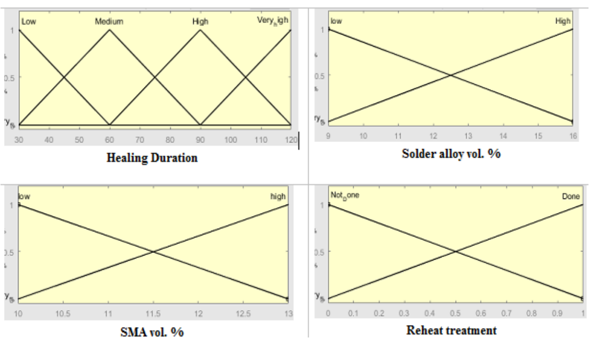


Figure 6. Linguistics variable for input membership functions

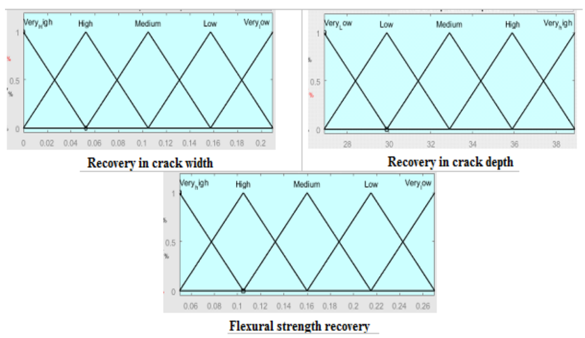


Figure 7. Linguistics variable for output membership functions

TABLE 5. Knowledge based rule formation based between input and output membership function

	Healing Duration		Solder alloy vol. %		SMA strip vol. %.		Reheat treatment		Normalized Crack width Recover %	Normalized Crack depth Recover %	Normalized Flexural strength Recover %
IF	L	&	L	&	L	&	D	**THEN**	M	L	M
IF	L	&	H	&	H	&	ND	**THEN**	VL	VL	VL
IF	M	&	L	&	L	&	ND	**THEN**	L	M	M
IF	M	&	H	&	H	&	D	**THEN**	L	M	H
IF	H	&	L	&	H	&	D	**THEN**	M	H	H
IF	H	&	H	&	L	&	ND	**THEN**	M	VH	VH
IF	VH	&	L	&	H	&	ND	**THEN**	L	H	H
IF	VH	&	H	&	L	&	D	**THEN**	VH	VH	VH

VL: VERY LOW; L: LOW; M: MEDIUM; H: HIGH; VH: VERY HIGH; D: DONE; ND: NOT DONE

smart composite was to keep its structural stability by reinforcing it with Ni-Ti wires, which mend macro cracks while the solder alloy binds micro-cracks by filling them with solder alloy. The focus of this research is to identify the factors that influence self-healing assessments. Furthermore, the principle of NDT utilizing ECT has been used to more effectively determine the crack depth [19, 21-22].

These experiments were initially done to test the self-healing properties of L8 mixed orthogonal array. The parameters and their levels considered for fabrication with different experimental runs is shown below in Table 6. For each experimental run, the resulting S/N ratio is utilized to determine the output membership functions' range as indicated in Table 7. Here the calculated S/N ratio is symmetric therefore normalizing for calculated S/N ratio was not considered. For deciding the range of output membership function, directly from S /N values the range was considered.

Figure 8 depicts an overall formulation of a Mamdani-based fuzzy interference system for forecasting the self-healing assessment. The following stage entails evaluating and configuring the input membership design properties function so that it may be displayed in the linguistic variables. In Figure 9, the crisp values of design parameters such as "Healing duration," "specimen size," "SMA vol. %," and "Diameter of wire" are fuzzified, whilst the fuzozy values. For example, the fuzzy set value for healing length as input design parameters is grouped into four categories: "Low," "Medium," "High," and "Very High."

TABLE 6. Input parameters selection with their considered levels

Parameters	Level 1	Level 2	Level 3	Level 4
Healing Duration (in min.)	30	60	90	120
Specimen size (mm) (Notations)	1 as (85X 11 X 10)	2 as (137 X 21 X 10)	-	-
SMA vol. (in %)	0.50	1.30	-	-
Diameter of SMA wires (in mm)	0.47	0.96	-	-

TABLE 7. A summarized table show the L8 orthogonal array experimental runs along with obtained healing assessments [19]

Healing Duration	Specimen size	SMA Vol.%	Dia. of SMA wires	Crack width Recovery %	S/N ratio	Crack depth Recovery %	S/N ratio	Strength Recovery %	S/N ratio
30	1	0.5	0.47	59.15	35.43	4.2	12.46	3.46	10.78
30	2	1.3	0.96	60.88	35.68	4.8	13.62	6.85	16.71
60	1	0.5	0.96	65.38	36.30	7.8	17.84	6.93	16.81
60	2	1.3	0.47	58.06	35.27	10.1	20.08	9.3	19.36
90	1	1.3	0.47	81.81	38.25	27.8	28.88	22.33	26.97
90	2`	0.5	0.96	76.55	37.67	11.9	21.51	35.73	31.06
120	1	1.3	0.96	100	40	96.9	39.72	73.76	37.35
120	2	0.5	0.47	77.1	37.74	43.1	32.68	44.89	33.04

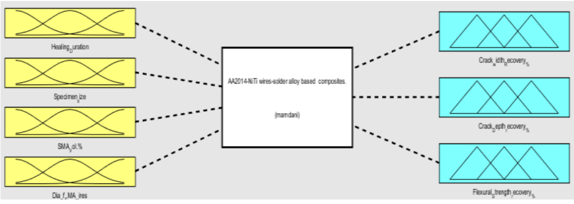


Figure 8. An overall Mamdani based fuzzy interference system for case study II

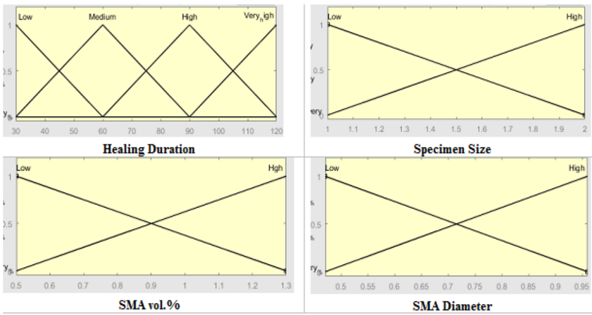


Figure 9. Linguistics variable for input membership functions

For healing assessments, the S/N ratio was regarded as a measurement performance of the output membership functions. An inference link is established between parametric combinations of experimental trails, as illustrated in Figure 10. Crack width recovery is categorized into linguistic terms such as crack width recovery is classified as "Very High", "High", "Medium", "Low", and "Very Low". A specific linguistics variable, called fuzzy set data, is employed by the expert to build a rule editor which describes how input and output membership functions relate to one another as shown in Table 8.

6. RESULTS AND DISCUSSION

The results obtained using regression correlations (based on the linear fit obtained using the following experimental data) for both case study is compared with developed fuzzy logic predictive rule based model. The model based on soft computing technique assists the designer to select optimal parameters for a design of higher self-healing assessments.

6. 1 Case Study-I To Predict Self-healing Assessments for AA2014-Niti Strip-solder Alloy Based Hybrid Structure After decision making unit through rule based database and de-fuzzification interface the crisp value of output membership function is evaluated. A summarized results for all predictive models used in the analysis is shown in Table 9. The evaluated results depicts an overall satisfactory performance of predictive fuzzy model in minimum experimental runs. An average of error obtained for crack width recovery % is 2.62 %, for crack depth recovery 0.09 % and for flexural strength recovery 2.37 %, respectively. The range selected by considering S/N ratio

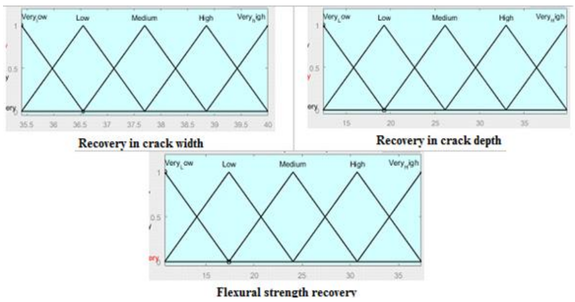


Figure 10. Linguistics variable for output membership functions

TABLE 8. Knowledge based rule formation based between input and output membership function

	Healing Duration		Specimen Size		SMA strip vol. %.		Dia. of SMA wire		Normalized Crack width Recover %	Normalized Crack depth Recover %	Normalized Flexural strength Recover %
IF	L	&	L	&	L	&	L	**THEN**	VL	VL	VL
IF	L	&	H	&	H	&	H	**THEN**	VL	VL	L
IF	M	&	L	&	L	&	H	**THEN**	L	L	L
IF	M	&	H	&	H	&	L	**THEN**	VL	L	L
IF	H	&	L	&	H	&	L	**THEN**	H	M	M
IF	H	&	H	&	L	&	H	**THEN**	M	L	H
IF	VH	&	L	&	H	&	H	**THEN**	VH	VH	VH
IF	VH	&	H	&	L	&	L	**THEN**	M	H	H

VL: VERY LOW; L: LOW; M: MEDIUM; H: HIGH; VH: VERY HIGH minimizes the range of fuzzy data set that facilitates the design expert to create more precise and accurate rule based model. The Negative S/N ratio for each experimental runs is further normalized to positive values for considering the range of the output membership functions. The Positive S/N ratio is directly considered for choosing the range of output membership function. The linear regression analysis done using Minitab 19 helped in formulation of regression equation for predicting the self-healing assessments. The dependent variable i.e. crack width recovery, crack depth recovery % and recovery in flexural strength is formulated with independent variables (i.e. healing duration, solder alloy vol. %, SMA strip vol. % and reheat treatment) using linear fit regression equation as described in Equations (15), (16) and (17), respectively.

$$Crack\ width\ recovery = 81.8 + (0.819 * H) + (0.620 * S_a) - (2.778 * S_s) + (12.15 * R) \quad (15)$$

$$Crack\ depth\ recovery = 60.4 + (0.4865 * H) + (1.384 * S_a) - (5.33 * S_s) + (5.74 * R) \quad (16)$$

$$Flexural\ strength\ recovery = 37.8 + (0.4626 * H) + (0.591 * S_a) - (3.21 * S_s) + (10.17 * R) \quad (17)$$

$H = Healing\ duration$

$S_a = Solder\ alloy\ vol.\%$,

$S_S = SMA\ strip\ vol.\%$,

$R = Reheat\ treatment$

TABLE 9. Summarized result for all experimental runs with predictive models

Healing Assessment	Experiment No	Experimental Normalized S/N Ratio	Fuzzy Normalized Predicted S/N Ratio	Experimental Observation	Fuzzy Predicted Model	Regression Analysis
Crack Width Recovery %	1	0.114	0.105	78.26	70.05	77.17
	2	0.207	0.193	64.28	58.84	61.03
	3	0.179	0.157	68.23	58.08	70.45
	4	0.139	0.157	74.22	81.95	78.61
	5	0.100	0.105	80.62	82.96	79.69
	6	0.110	0.104	78.98	73.96	80.22
	7	0.147	0.157	73.01	77.01	72.97
	8	0	0	100	100	97.80
Crack Depth Recovery %	1	31.57	29.9	37.89	39.45	39.90
	2	26.93	27.9	22.21	22.83	27.85
	3	34.13	32.9	50.89	49.02	48.75
	4	34.63	32.9	53.95	55.91	48.18
	5	34.78	35.9	54.87	56.64	53.09
	6	37.89	37.9	78.45	78.39	73.03
	7	35.57	35.9	60.06	60.68	61.95
	8	38.87	37.9	87.85	85.51	93.36
Flexural strength Recovery %	1	0.15	0.162	35.94	37.63	35.06
	2	0.27	0.262	15.76	14.75	19.40
	3	0.15	0.162	36.2	38.14	38.77
	4	0.12	0.105	45.4	37.77	43.45
	5	0.08	0.102	55.96	63.87	53.19
	6	0.06	0.061	64.08	57.63	56.80
	7	0.08	0.102	56	63.97	56.90
	8	0.05	0.061	75.4	86.12	80.83

An effectiveness in fuzzy logic approach compared with experimental data shows significant improved results as shown in Table 9. Recovery in flexural strength % has shown the highest error due to more variation and non-linearity in the data sets. Although with only 8 experimental runs and less number of data sets an average of 3.48 % shows that proves that fuzzy logic approach is capable of predicting the self-healing assessments that assists in estimating the best possible combination of input parametrical design. The rule editor of the formulated fuzzy model for experiment no. 3 conditions is shown in Figure 11.

The residual plot for self-healing assessment is shown in Figure 12 whereas error analyis is shown in Figure 13. Further, in order to validate the predictive model with the statistical model error analysis is done using MAPE, MSE and RSME. The analysis shown that for each error analysis recovery in crack depth has shown less error in compared to linear regression model. Hence, formulated fuzzy model is feasible and able to predict the healing assessment results more accurately and precisely as shown in Figure 14.

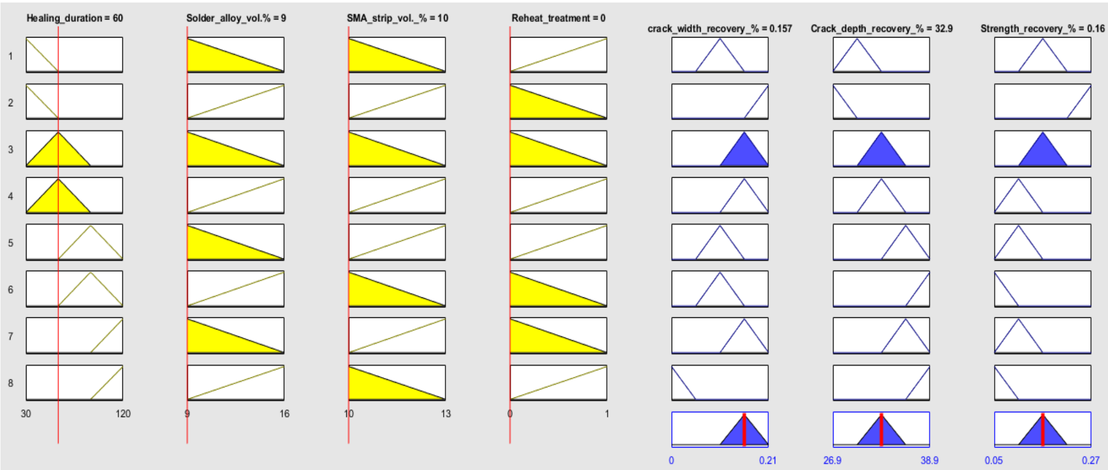
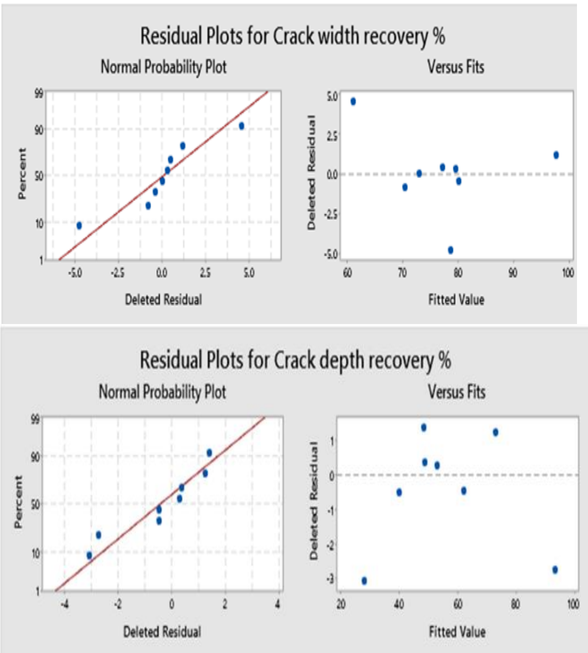


Figure 11. The fuzzy based rule editor dialog box result for experimental no. 3



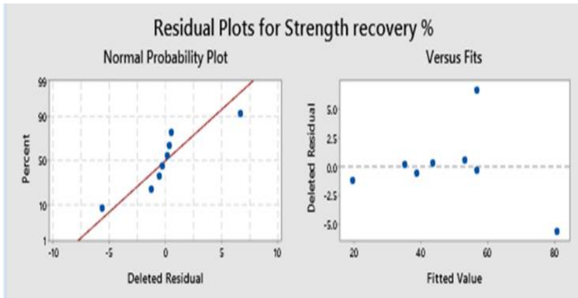


Figure 12. Linear fit and Residual plot of different experimental runs for all the healing assessments

6. 2. Case Study-II: To Predict Self-Healing Assessments for AA2014-Niti Wire-Solder Alloy Based Hybrid Composites

After primary investigation of the parameters controlling the self-healing assessments, the formulated fuzzy predictive model (based on the rules) assists in determining the healing assessments. The soft computing technique helps to establish the relation between input and output

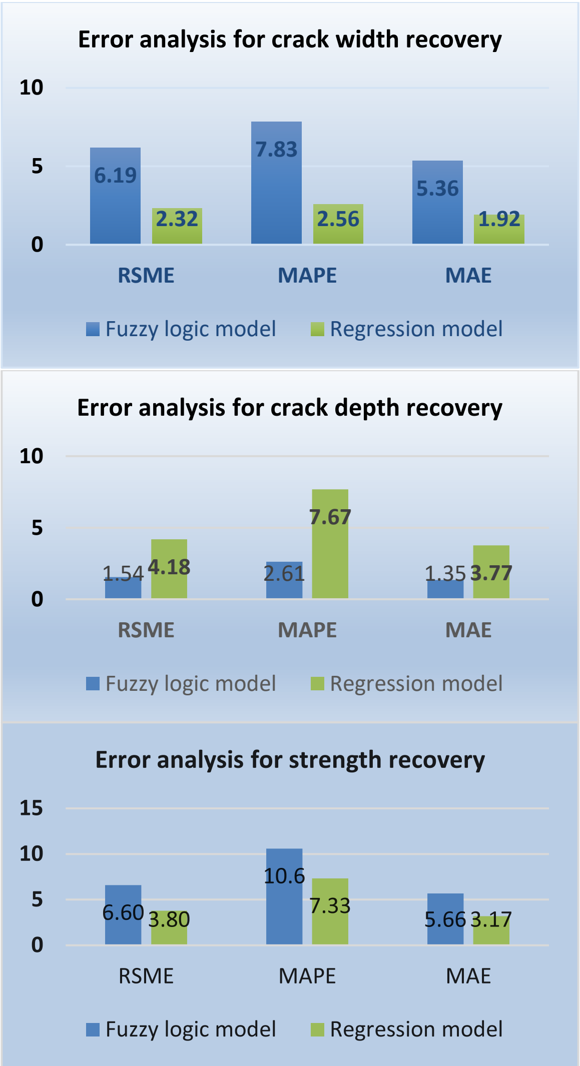


Figure 13. A comparative error analysis for different predictive model for different healing assessments

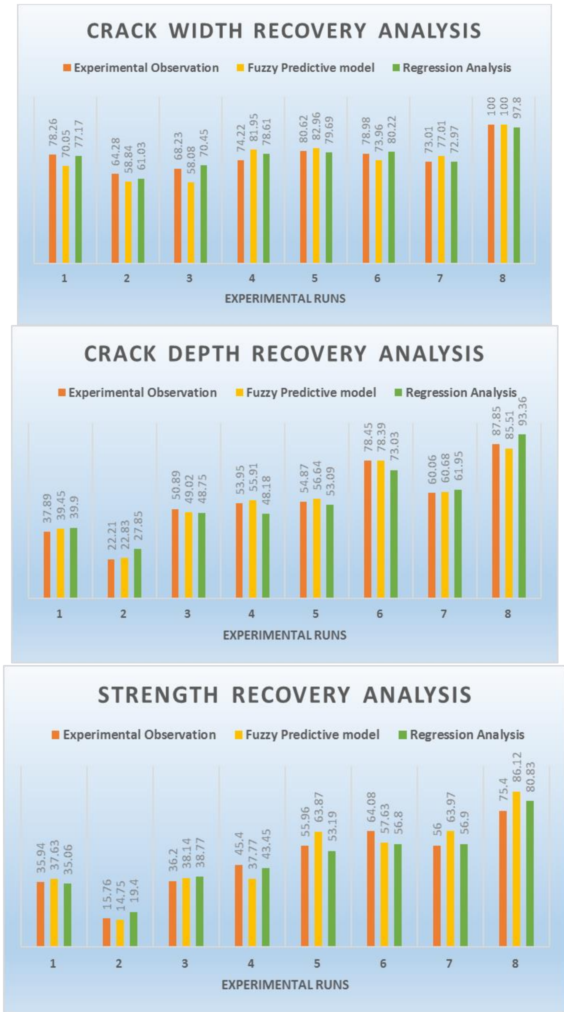


Figure 14. A summarized comparison of healing assessments for different predictive model with actual experimental observations

responses. The input membership functions i.e. healing durations, specimen size, SMA vol. % and Diameter of SMA wires has a large control over healing of the damaged structure. An average error is obtained for crack width recovery % is 0.10%, for crack depth recovery 2.80% and for flexural strength recovery 1.75%, respectively. The results obtained using predictive model is shown in Table 10. It is observed that with more variation in experimental observation the error is estimated to be more. Using S/N ratio for each experimental runs the variation in the data sets is lowered due to which predicted results is estimated to be closer to the experimental observations. The rule editor of the formulated fuzzy model for experiment no. 8 conditions is shown in Figure 15.

The dependent variable i.e. crack width recovery, crack depth recovery % and recovery in flexural strength is formulated with independent variables (i.e. healing duration, Specimen size, SMA vol. % and Dia. of SMA wire) using linear fit regression equation as described in Equations (18), (19) and (20), respectively.

$$Crack\ width\ recovery = 43.2 + (0.3435 * H_d) - (8.44 * S_s) + (7.05 * SMA_{vol\%}) + (13.62 * SMA_{dia}) \tag{18}$$

$$Crack\ depth\ recovery = -45.6 + (0.731 * H_d) - (10.7 * S_s) + (15.2 * SMA_{vol\%}) + (30.7 * SMA_{dia}) \tag{19}$$

$$Flexural\ strength\ recovery = -38.6 + (0.611 * H_d) - (2.433 * S_s) + (6.6 * SMA_{vol\%}) + (22.1 * SMA_{dia}) \tag{20}$$

$H_d = Healing\ Duration$

$SMA_{vol.\%} = SMA\ vol\ \%$

$SMA_{dia} = Diameter\ of\ SMA\ wire$

$S_s = Specimen\ Size$

TABLE 10. Summarized result for all experimental runs with predictive models

Healing Assessment	Experiment No	Experimental S/N Ratio	Fuzzy Predicted S/N Ratio	Experimental Observation	Fuzzy Predicted Model	Regression analysis
Crack Width Recovery %	1	35.43	35.6	59.15	59.43	55.00
	2	35.68	35.6	60.88	60.74	58.86
	3	36.30	35.6	65.38	64.09	71.97
	4	35.27	35.6	58.06	58.59	62.49
	5	38.25	38.8	81.81	82.96	81.24
	6	37.67	37.6	76.55	76.40	73.83
	7	40	39.6	100	98.98	98.22
	8	37.74	37.6	77.1	76.81	77.46
Crack Depth Recovery %	1	12.46	11.6	4.2	3.88	-10.52
	2	13.62	14.7	4.8	5.15	0
	3	17.84	19.3	7.8	8.39	19.27
	4	20.08	19.3	10.1	9.69	11.66
	5	28.88	26.1	27.8	24.83	49.09
	6	21.51	19.3	11.9	10.53	23.30
	7	39.72	37.5	96.9	91.16	78.89
	8	32.68	32.9	43.1	43.38	34.96
Flexural strength Recovery %	1	10.78	12.9	3.46	4.02	-9.01
	2	16.71	17.4	6.85	7.12	4.66
	3	16.81	17.4	6.93	7.16	20.14
	4	19.36	17.4	9.3	8.25	12.16
	5	26.97	24.1	22.33	19.67	32.92
	6	31.06	30.7	35.73	35.31	36.04
	7	37.35	35.2	73.76	69.25	62.08
	8	33.04	30.7	44.89	41.46	43.54

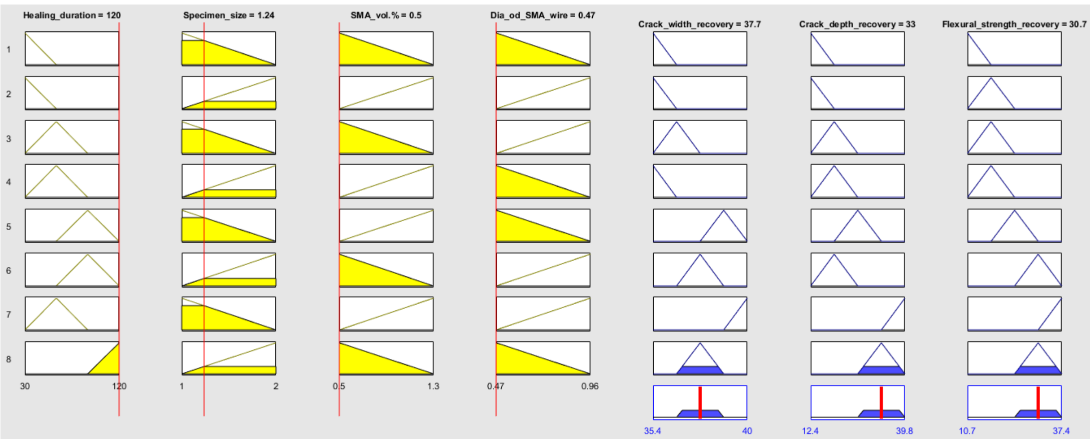


Figure 15. The fuzzy based rule editor dialog box result for experimental no. 8

The obtained results after implementing fuzzy logic model and regression analysis is compared using error analysis. The results observed from Fuzzy logic model shown a tremendous forecasting in predicting the experimental observation built on knowledge based rule in compared to regression analysis. The errors analyses (i.e. RSME, MAPE, MAE) show more error in regression analysis for all self-healing assessments. The residual plot for self-healing assessment is shown in Figure 16. The summarized error analysis is shown in Figure 17. The analysis concludes the fuzzy predictive knowledge based model to be versatile and precise that can be seen in Figure 18.

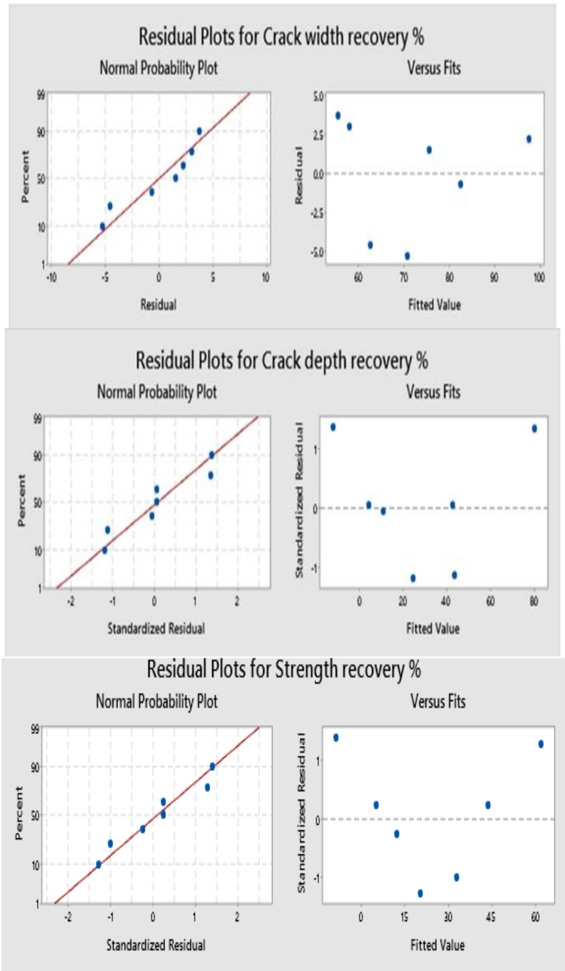
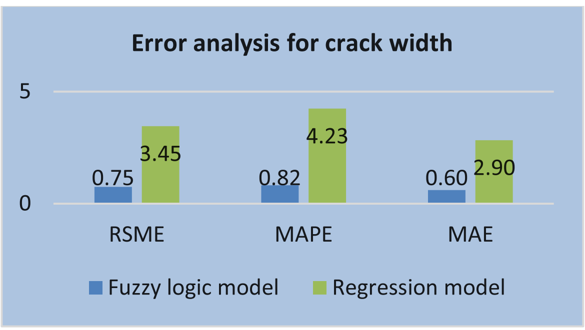


Figure 16. Linear fit and Residual plot of different experimental runs for all the healing assessments



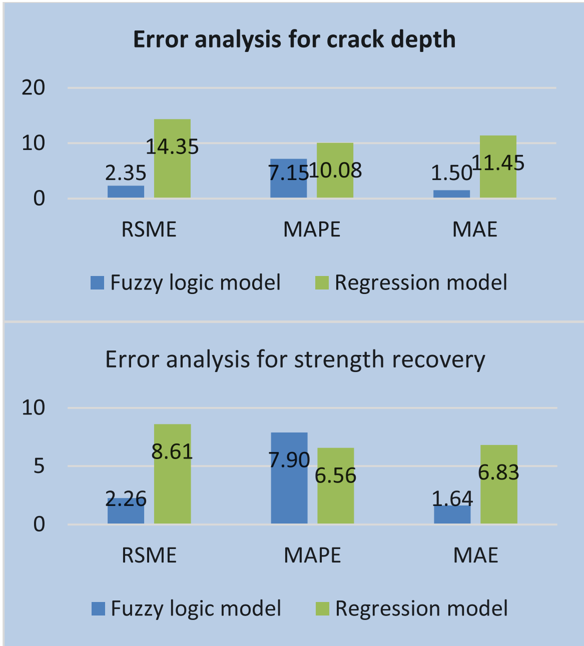


Figure 17. A comparative error analysis for different predictive model for different healing assessments

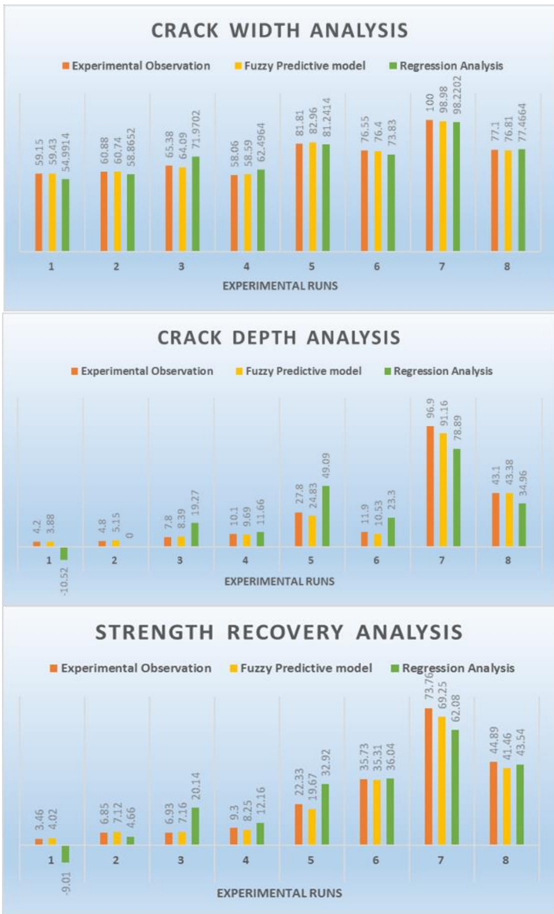


Figure 18. A summarized comparison of healing assessments for different predictive model with actual experimental observations

7. CONCLUSIONS

The study involves the design of a hybrid self-healing composite metallic structure through Fuzzy logic model for predicting the self-healing assessments. The predictive fuzzy model rules were formed between input and output membership function by utilizing S/N ratio using ANOVA analysis for every experimental runs. Further, the error analysis were performed using statistical tool (i.e. RSME, MAPE and MAE) to compare the error associated with fuzzy logic model and linear regression model. The observations drawn from the research are as follows:

1. The fuzzy logic model developed with the formulated S/N ratio has led to an accurate self-healing assessment predictions even with less number of experimental runs. The predictive fuzzy model results may further be improved by increasing the experimental runs for the analysis.
2. Fuzzy logic model has closely predicted the self-healing assessment of various structures with their respective experimental observations. For case study I, an average of about 6.33 % error in prediction of recovery in healing assessments was obtained by implementing fuzzy logic model.
3. For case study I, the comparative error analysis has shown good results for predicting recovery in crack depth compared to linear fit regression model. Based on S/N ratio obtained using ANOVA analysis, rules were formed that limit the large variations output responses range. This helps the domain expert in formulating the precise rules between input and output membership functions and evaluating the healing assessments more accurately.
4. For case study II for all healing assessments, fuzzy rule-based model has proved to be the best predictive model compared with linear regression model. An average error of about 4.94 % for recovery in healing assessments was observed after implementing fuzzy logic model. The error analysis resulted in lower error values for fuzzy model on contrary to higher error using linear regression model.
5. The analysis for case studies were performed for the fixed range of various input parametric design for designing the self-healing composite structure. However, other input parameters influencing the higher self-healing assessments can also be studied experimentally to overcome the limitations in healing of the structure and new predictive fuzzy based model can be formulated. As a future scope, other machine learning based predictive models like Artificial Neural Fuzzy interference system (ANFIS) and artificial neural network (ANN) can be compared simultaneous to analyze the effective design of self-healing composites. Large number of experimental runs generally L27 orthogonal array Taguchi design shall improve the predictability of machine learning based models with less variation in errors.

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Persian Abstract

چکیده

ایده ای برای ترمیم سطح آسیب دیده از طریق عوامل ترمیم کننده در کامپوزیت فلزی در مرحله توسعه است. بنابراین، انتخاب پارامترهای طراحی برای نسل جدید کامپوزیت هوشمند پیچیده تر و دشوارتر است. در مطالعه حاضر، دو مطالعه موردی در مورد سازه های هوشمند خود ترمیم شونده با پارامترهای طراحی ورودی مختلف برای ارزیابی خواص درمانی گنجانده شده است. آزمایش‌های L-8 مبتنی بر تاگوچی برای تجزیه و تحلیل پارامترهای تأثیرگذار مسئول ارزیابی‌های خود ترمیمی بالاتر (یعنی بازیابی در عرض ترک، بازیابی در عمق ترک و بازیابی مقاومت خمشی) انجام شد. برای ارزیابی ارزیابی های خود ترمیمی سازه آسیب دیده، یک تکنیک محاسباتی نرم افزار بر اساس نسبت S/N از تجزیه و تحلیل ANOVA به دست می آید. نتایج تجربی بیشتر برای ساخت مدل پیش‌بینی منطق فازی در نظر گرفته شد. مدل‌های رگرسیون خطی، یعنی یک ابزار آماری برای قضاوت در مورد دقت مدل پیش‌بینی‌شده مبتنی بر فازی از طریق تحلیل‌های خطای مختلف، تولید می‌شود. بر اساس مدل منطق فازی نسبت S/N، نتایج مقادیر خطای کمتری ٦.٣٣ و ٤.٩٤ درصد را برای مطالعات موردی I و II در مقایسه با مدل رگرسیون اقتباس شده برای همه ارزیابی‌های خود درمانی نشان می‌دهند. این مدل شباهت نزدیکی با مشاهدات تجربی حتی با تعداد کمتری از اجراهای آزمایشی ارائه می دهد. این نتیجه می‌گیرد که مدل منطق فازی یک ابزار محاسباتی نرم افزار قدرتمند برای انجام کارهای تحقیقاتی بزرگ مربوط به طراحی پارامترهای ورودی برای سازه‌های کامپوزیت خود ترمیم شونده مبتنی بر فلز در آینده نزدیک فراهم می‌کند.