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Research article

Study of factors affecting the magnetic sensing capability of shape memory alloys for non-destructive evaluation of cracks in concrete: Using response surface methodology (RSM) and artificial neural network (ANN) approaches

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A R T I C L E I N F O

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A B S T R A C T

Currently, the field of structural health monitoring (SHM) is focused on investigating non-destructive evaluation techniques for the identification of damages in concrete structures. Magnetic sensing has particularly gained attention among the innovative non-destructive evaluation techniques. Recently, the embedded magnetic shape memory alloy (MSMA) wire has been introduced for the evaluation of cracks in concrete components through magnetic sensing techniques while providing reinforcement as well. However, the available research in this regard is very scarce. This study has focused on the analyses of parameters affecting the magnetic sensing capability of embedded MSMA wire for crack detection in concrete beams. The response surface methodology (RSM) and artificial neural network (ANN) models have been used to analyse the magnetic sensing parameters for the first time. The models were trained using the experimental data obtained through literature. The models aimed to predict the alteration in magnetic flux created by a concrete beam that has a 1 mm wide embedded MSMA wire after experiencing a fracture or crack. The results showed that the change in magnetic flux was affected by the position of the wire and the position of the crack with respect to the position of the magnet in the concrete beam. RSM optimisation results showed that maximum change in magnetic flux was obtained when the wire was placed at a depth of 17.5 mm from the top surface of the concrete beam, and a crack was present at an axial distance of 8.50 mm from the permanent magnet. The change in magnetic flux was 9.50 % considering the aforementioned parameters. However, the ANN prediction results showed that the optimal wire and crack position were 10 mm and 1.1 mm, respectively. The results suggested that a larger beam requires a larger diameter of MSMA wire or multiple sensors and magnets for crack detection in concrete beams.

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1. Introduction

Cracks in concrete buildings are a result of mechanical or environmental stresses, which contribute to the eventual breakdown of infrastructures. These structural failures and breakdowns cause a lot of financial losses, human fatalities and property damages [1]. Therefore, it is extremely important to identify and promptly prevent cracks in concrete buildings. Historically, cracks in civil constructions have been identified by physical inspections; however, these methods fail to indicate the existence of internal cracks in the structures [2]. This highlights the need for non-destructive monitoring devices or techniques that can be employed for the evaluation of internal cracks in concrete buildings. The researchers have devoted considerable attention to the field of non-destructive structural health monitoring (SHM) techniques for comprehending the internal defects in concrete structures [3]. This has been achieved through the development of improved non-destructive assessment techniques, such as piezo-electrics, acoustic emission, magnetic sensing, strain sensors and visual inspection [4,5].

Magnetic sensing has gained significant interest in recent decades as a relatively new non-destructive evaluation method applicable to SHM [6]. It involves assessing the changes in the external magnetic field due to the propagation of internal damages in concrete structures. Typically, sensors are used to detect the changes in external magnetic fields. These sensors include the embedded inductive magnetic sensors or large magneto-resistive sensors [7]. Large magneto-resistive sensors, with their low energy consumption and wide sensing range, have been suggested as a viable magnetic sensor for non-destructive evaluation of defects in internal steel bars [8]. The literature showed that magnetic sensing technology has been discussed for the evaluation of steel corrosion or cracks in steel bars [9]. However, the detection of cracks in concrete structures using magnetic sensing techniques is not well developed yet and needs attention.

A study [10], showcased the first evidence of the efficacy of embedding magnetic shape memory alloy (MSMA) wire in a concrete beam for the purpose of detecting internal cracks using magnetic sensing. MSMAs are renowned for their capacity to modify magnetic and other characteristics through phase transitions [11,12]. Embedding MSMA wires into concrete structures offers the opportunity to assess their structural integrity through the use of external magnetic field detection and also provides strength to concrete by providing reinforcement [13]The study suggested that the presence of a crack in a concrete beam produces a stressed area within an embedded MSMA wire. This stressed area can modify the external magnetic flux density in proximity to the stressed region. The giant magnetoresistive sensor can measure the change in magnetic flux density. The study also suggested that sensor and MSMA wire position play an important role in the magnetic flux density variation and crack detection in concrete beams.

However, no study further explored the correlations and interactions between the change in magnetic flux density and embedded MSMA wire-concrete composite for magnetic sensing of cracks in concrete structures. Also, there is no developed relationship between the magnetic sensing capability of MSMA wire and the factors affecting its capability. Whereas MSMA are the potential material for the magnetic sensing of concrete damages. These materials do not significantly impact the magnetic field produced by a permanent magnet unless stressed due to cracks or damages in concrete. Consequently, any alterations detected by the sensing system are attributed solely to localised stress changes occurring within the embedded MSMA [10]. Therefore, MSMAs must be explored in the field of magnetic sensing of cracks in concrete structures.

The current study aimed to analyse the correlations between the impacting factors on crack detection in beams such as beam size, MSMA wire diameter, MSMA wire position, crack location, magnet and sensor position and the affected parameters, such as magnetic flux density and change in the magnetic field, which operate as the independent and dependent variables, respectively. This aim was achieved by monitoring the generated magnetic flux when moving a magnet, wire and a sensor along the surface of the structural element.

To save the cost of lab experiments, computer-based models are used to correlate the independent and dependent variables [14]. The most important stages in correlating process parameters are modelling and optimisation, which increase the system's efficiency without increasing the cost. Crack detection in concrete using magnetic sensing is a complex process involving multiple variables and non-linear correlations. To obtain the optimum experimental conditions, a reliable and simple method must be used to correlate the parameters in the magnetic sensing method. The conventional optimisation approach (single variable optimisation) is time-consuming and inefficient since it fails to capture the full impact of process parameters and their interactions. This strategy can also misread results. Statistics have been utilised to solve this problem. Recent interest has focused on response surface methodology (RSM), a set of mathematical and statistical methods for assessing the effects of several independent factors.

RSM examines the link between response(s) and independent factors and determines how they affect processes [15]. This approach is cheaper, requires fewer experiments, studies parameter-response interaction, predicts response, checks method appropriateness, and takes less time. Low-order polynomial equations in a predefined area of the independent variables is examined to find the optimal answers [16].

Over the past decade, data analysis methods based on biological phenomena have also become popular for modelling methodologies, including artificial intelligence and evolutionary computing. Indeed, an artificial neural network (ANN) is a massively linked network of basic processing components that can process input in parallel. This strategy works when process performance mechanisms are complicated [17]. Recently, ANNs have been extensively explored for structural analysis due to their dependable and effective ability to capture non-linear correlations between variables. They solve difficulties that standard statistical approaches cannot. ANNs are considered due to their widespread application and capacity to tackle complex issues [18]. They are used in engineering for process modelling and simulation. Therefore, RSM and ANN have been chosen for this study to analyse and predict the most suitable parameters for crack detection in concrete beams.

The application of RSM and ANN in multiple fields has successfully been demonstrated [19]. However, their application in magnetic sensing methods has not yet been evaluated. Hence, this study is the first of its kind to investigate the parameters affecting the magnetic sensing capability of MSMA using computer-based methodologies. These models would help to validate the significance of MSMA reinforcement in concrete structures for non-destructive evaluation of the cracks.

To date, there has been a lack of research on the exploration of MSMAs for magnetic sensing in concrete structures, and there is currently no established procedure for external non-destructive evaluation of the proposed type. Therefore, it is imperative to do a detailed analysis of the impacting factors, such as MSMA wire position, crack location, magnet and sensor position and the affected parameters, such as magnetic flux density and change in the magnetic field, which operate as the independent and dependent variables, respectively. This would be achieved by monitoring the generated magnetic flux when moving a magnet, wire and a sensor along the surface of the structural element. To save the cost of lab experiments, it is best to use computer-based models to correlate these independent and dependent variables.

2. Related works

The application of magnetic sensing in non-destructive assessment is a study field that intrinsically encompasses several disciplines, encompassing both computational and experimental domains [7]. Accurate results in magnetic sensing rely on the precise alignment of the magnetic field. This alignment is particularly important when using ferromagnetic materials, which are generally required for magnetic sensing. These materials also serve the purpose of providing extra structural support.

Shape memory alloys (SMAs) are versatile ferromagnetic materials that undergo a transition from the austenite phase to the martensite phase when subjected to stress or changes in temperature [20]. These modifications lead to significant recoverable deformations and modify the physical characteristics. SMA wires, when encompassed into concrete structures, enhance the longevity of the structures by utilising their pseudo-elastic characteristics. SMAs also demonstrate reusability, which is advantageous given their higher production costs compared to structural steel [21]. Additionally, they exhibit excellent resistance to corrosion and mitigate the propagation of fatigue cracks. The use of embedded SMA components for damage detection is appealing because of their enhanced longevity, structural strengthening, and reusability in contrast to conventional sensing techniques. The application of SMAs in filling internal cracks, reinforcing structures, and mitigating fatigue caused by cyclic stress has made their inclusion in structural evaluation highly desirable. Hence, it is necessary to assess the use of SMAs for magnetic sensing in both the structural and magnetic aspects.

The MSMAs, a class of SMAs, may effectively modify magnetic fields by virtue of their altered permeability in response to internal stress. Ferromagnetic SMAs, such as FeMnAlNi alloys, have been engineered to possess the necessary strength for structural reinforcement, as well as a capability to regain their original shape after undergoing significant deformation, known as a recoverable super elastic effect [22].

RSM is a very successful statistical analytic technique that is widely used in the field of concrete materials [23]. RSM is used to predict and simulate the characteristics of concrete materials under various parameters, using diverse materials. It is employed not only for experimental design but also for analysing the mathematical relationship between the elements that influence the process and the resulting responses.

ANN is a paradigm for information processing that models the way biological nerve systems, such as the brain, process information [24]. The most notable characteristic of this paradigm is its innovative framework for processing data. The system consists of several interconnected processing units known as neurons, which collaborate to tackle specific problems. Neural networks are employed to extract patterns and identify trends from data that is too intricate for humans or other computer systems to comprehend due to their remarkable ability to deduce meaning from imprecise or complex data [25]. An "expert" neural network analyses a certain type of data. You may then use this expert to forecast intriguing new events. Training with large amounts of data can prevent overfitting and make ANN fault-resistant with redundancy and superior learning approaches. An overfitted or over-learned network cannot perform better with unclassified test data but may categorise training material [26]. Overfitting may be prevented by using a lot of data for training and configuring the network's size and structure to handle it. When a less complicated network analyses massive amounts of data with mismatched training, underfitting occurs. Thus, choosing an ANN trained with sufficiently important data and a learning technique suitable for structural degradation detection is of great relevance. ANN has been used in various studies for the assessment of structural cracks [27,28], concrete and steel bridges SHM [29,30], seismic retrofitting in reinforced concrete structures [31], and detecting damages [32,33]. However, no application of RSM and ANN has been found in the magnetic sensing technique of embedded MSMA wires.

3. Materials and methods

Assessing changes in the surrounding magnetic field is necessary for SHM, utilising magnetic sensing, in order to ascertain the condition of the internal structure. Section S1 in supplementary materials determines the methodology for the structural and magnetostatic analysis for modelling the induced stresses in MSMAs under crack detection. The RSM and ANN models are developed to evaluate the data obtained from magnetostatic modelling and available literature. The models have the capability to predict the relationship between parameters impacting the magnetic sensing in concrete structures, while using the MSMA wire as reinforcement.

3.1. Response surface methodology modeling

The design of experiments was developed using Design Expert software for RSM modelling. A central composite design was selected. The independent variables were taken as the axial distance between the permanent magnet and the crack tip (D1) and the vertical distance between the permanent magnet and the wire (D2). The dependent variable was taken as a change in magnetic flux

(%). The axial distance D1 was taken as the +ve value on the right side of the magnet and the -ve value on the left side of the magnet, as shown in Fig. 1.

The ranges of D1 and D2 are presented in Table 1. The output dataset was taken from the literature [10] and magneto-static modelling according to the design of experiments. A total of 16 runs were obtained, shown in Table 1. The model was run, and the data was optimised.

3.2. Neural network modeling

The ANNs are effective predictive models that replicate the functioning of brain neural networks, detecting patterns and relationships within complex data sets, even when the underlying principles are unknown [33]. An ANN typically has many layers, including an input layer, an output layer and a hidden layer. The input layer takes the data that has to be analysed in order to identify patterns. The output layer of the ANN provides the data, which represents the values of the model's calculated outputs. The input data undergoes processing within the hidden layers to produce the output values. The number of neurons in the hidden layer is selected based on the hit-and-trial method and depends on the intricacy of the input and output relationship [28]. A two-layered feedforward backpropagation (FFBP) neural network is highly efficient for prediction models. The Levenberg-Marquardt method is frequently employed for such models due to its rapid convergence rate.

A dataset with inputs (distance from magnet to crack tip and position of wire) and outputs (change in magnetic flux) was used to develop an FFBP ANN model in this study. 27 data points were obtained from the literature. As no specific design of experiments is required, therefore more data points were obtained. 19 points (70 %) were used for the training of the model, 4 points (15 %) for validation and 4 points (15 %) for the testing of model. The transfer function was tan-sigmoid, while the number of neurons tested were ranged from 2 to 20. The training algorithm was taken as Levenberg-Marquardt. The model had a layer of connected nodes or neurons. The input layer received data, and the output layer provided the intended change in magnetic flux. The model was trained repeatedly after feeding the data. The performance of the model was evaluated by widely used mean square error (MSE) and regression coefficient (R). The schematic diagram of the input and output parameters of the ANN model can be seen in Fig. 2.

4. Results

These outcomes of the structural and magnetic modelling are presented in this section. The RSM and ANN modelling results are also presented with sufficient discussion to describe the results.

4.1. Stress analysis on crack tip

The structural model evaluates the stress propagation as a fracture occurs within a concrete beam. The stress distribution is shown in Fig. 3(a and b), developed by using DIANA finite element analysis software under 3-point loading conditions and MSMA wire reinforcement. The analysis showed that the stress on the concrete is transmitted to the wire, particularly near the crack's tip, as denoted by the light blue colour in Fig. 3(b). The crack propagation causes stress in small sections of the wire near the crack tip. The model also showed a stress and intensity factor rise around the crack tip, which may compromise the cohesiveness between the wire and concrete. This rise in stress in MSMA wire may cause a change in external magnetic flux.

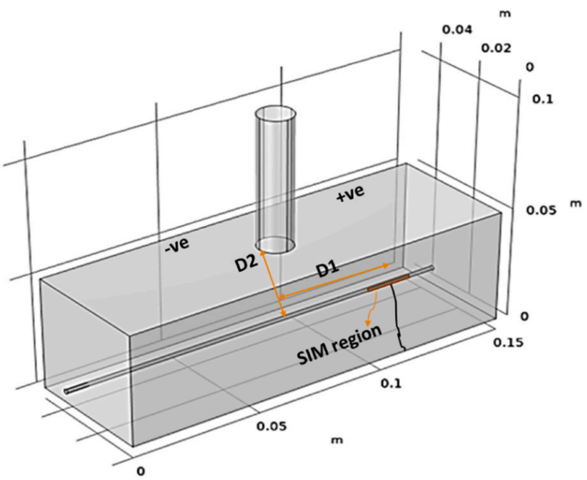

Fig. 1. Representation of input parameters.

Table 1
Data ranges of independent variables and design of experiments using RSM.

Variables		Code	Unit	Minimum	Maximum
Axial distance between permanent magnet and crack tip (D1)		A	mm	−70	70
Vertical distance between permanent magnet and the wire (D2)		B	mm	15	45
Run	D1	D2		Response	
1	0	30		6.5	
2	0	15		17.5	
3	70	15		1.46103	
4	−25	45		2.2	
5	70	15		2.46103	
6	−70	30		1.7904	
7	−70	45		1.0904	
8	25	45		2.2	
9	0	45		3.5	
10	70	45		1.0997	
11	70	30		1.24	
12	−45	15		3.643	
13	0	30		6.48	
14	−70	15		1.46103	
15	−70	45		1.0904	
16	0	30		6.46	

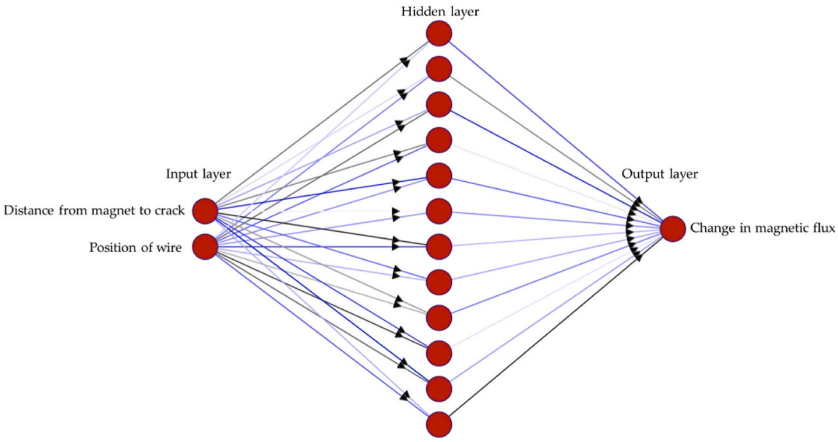

Fig. 2. Architecture of ANN.

4.2. *Magnetic field flux*

The evaluation and simulation of magnetic sensing were conducted using the finite element approach implemented in COMSOL magneto-statics. The presented model showcased the sensing abilities of an external magnet in conjunction with a sensor that detects alterations in the internal magnetisation of the MSMA wire. Based on magnetic testing calibration data acquired from experimental testing provided by Davis et al. [10], the magnetic properties of the MSMA wire were determined. The model computed the normal magnetic flux density for a permanent magnet, considering a probe moving away from the magnet along its polar axis. The results are shown in Fig. 4, with the analytical solution given as equation S6 in supplementary materials. The results showed that magnetic flux strength reduced with the increasing axial distance of the sensor. Several sensor positions were evaluated to assess the impact of sensor placement on the possible capacity to measure the magnetic field.

4.3. *Change in magnetic flux versus position of crack tip*

To assess the change in magnetic flux in the vicinity of a fracture, the magnetic wire is placed at various locations inside the concrete beam. The results are depicted in Fig. 5, which illustrates the change in magnetic flux with the change in distance between the magnet and crack tip while placing wires at distances of 15 mm, 30 mm, and 45 mm from the surface of the beam.

The maximum change in magnetic flux was observed at a distance of around 10 mm between the magnet and crack tip. Increasing the distance further in either direction reduced the change in magnetic flux.

As the MSMA wire was inserted deeper, the change in magnetic flux was reduced. When an MSMA wire is placed 45 mm below the surface, the typical magnetic flux density decreases by 2.5 %. Although extending the distance will result in a further reduction in

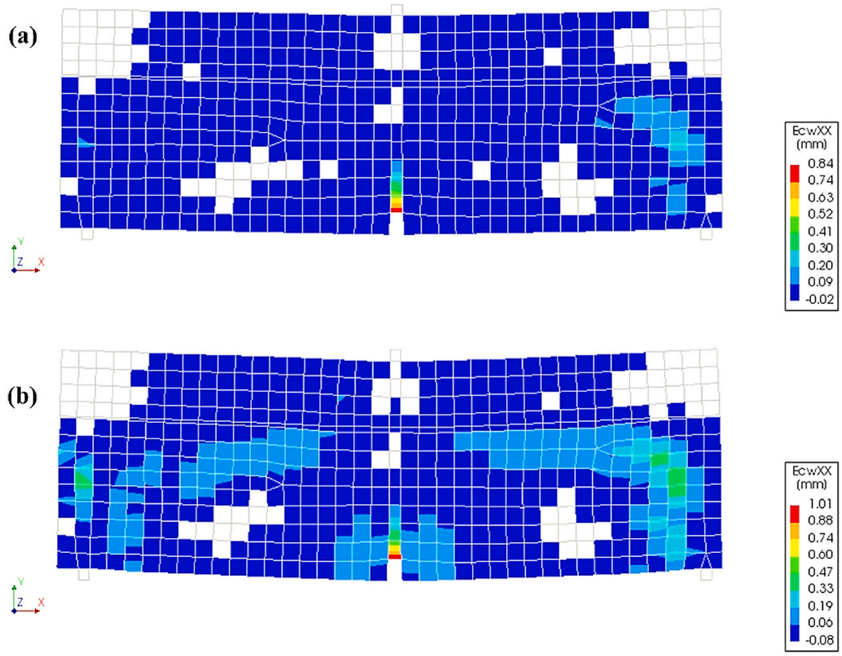

Fig. 3. Increased loading on the wire centered on the crack tip; (a) initial loading and (b) final loading.

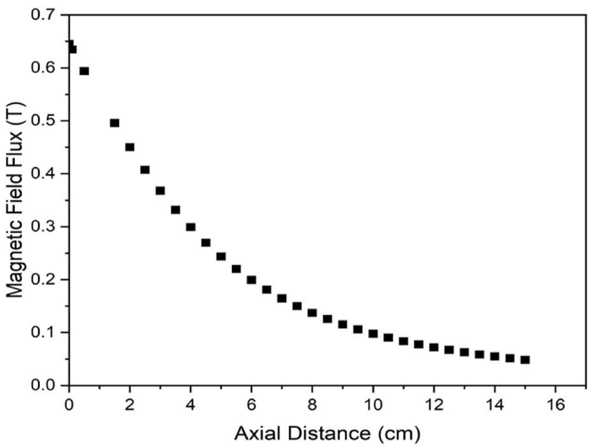

Fig. 4. Analytical outcomes of Magnetic Field Flux vs the axial distance.

signal intensity, it is crucial to acknowledge that all outcomes are based on the presence of a wire with a radius of 1 mm. Enlarging the diameter will significantly enhance signal strength because of the large augmentation in magnetisable volume. The complex relationship between the crack position, MSMA wire position and magnet position can be modelled using RSM and ANN.

4.4. RSM modeling outputs

4.4.1. Analysis of variance (ANOVA)

The study aimed to study the impact of independent factors, including crack tip distance from the magnet and MSMA wire distance from the magnet, on forecasting the change in magnetic flux for magnetic sensing of concrete cracks under increased loading. Response surface optimal design was used for this. ANOVA analysis was used to assess the significance of the developed model and its terms at a 95 % confidence level. The ANOVA analysis findings are displayed in Table 2. The model's high F-value of 10.50 demonstrated the strong importance of the independent variables. Both the model and model terms in this investigation have P-values <0.0500, as seen in Table 2. The key factors that contributed to the change in the magnetic flux model are A, B, A^2, A^2B, and A^3. The ultimate model, referred to as the cubic equation, is given in Equation (1). A lack of statistical significance in the lack of fit indicates that the model has a higher level of predictive power.

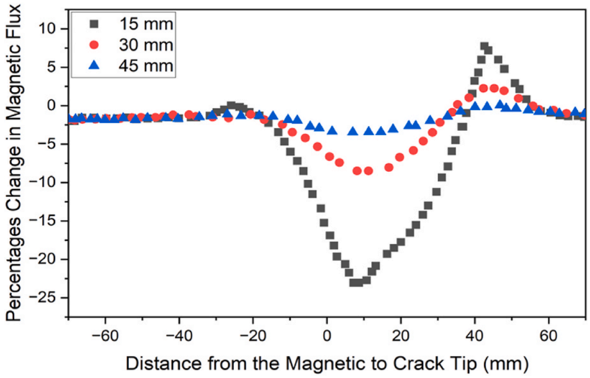

Fig. 5. Percentage change in normal magnetic flux versus Distance from Magnet to the MSMA wire for measuring the magnetic sensing.

Table 2
ANOVA for the developed model.

Source	Sum of Squares	df	Mean Square	F Value	p-value	
Model	76.03	8	9.5	10.5	0.0028	significant
A-D1	5.76	1	5.76	6.37	0.0396	
B-D2	7.71	1	7.71	8.51	0.0224	
AB	0.8357	1	0.8357	0.9231	0.3687	
A^2	36.8	1	36.8	40.65	0.0004	
B^2	2.54	1	2.54	2.8	0.138	
A^2B	5.09	1	5.09	5.62	0.0496	
AB^2	0.0243	1	0.0243	0.0268	0.8745	
A^3	6.21	1	6.21	6.86	0.0344	
B^3	0	0				
Residual	6.34	7	0.9053			
Lack of Fit	6.34	1	6.34	18274.09	0.1	
Pure Error	0.0021	6	0.0003			
Cor Total	82.36	15				

$$Y = -6.17 - 5.22A + 2.68B + 4.09A^2 - 2.60A^2B + 5.31A^3 \tag{1}$$

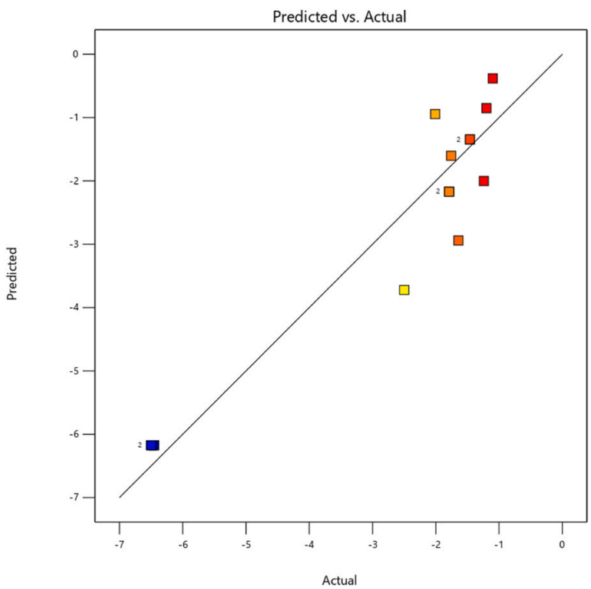

Fig. 6. Predicted and actual value of change in magnetic flux.

4.4.2. Analysis of model adequacy

The projected model's adequacy, fitness, and consistency are assessed using R^2. A high predicted or adjusted R^2 around unity suggests significant model-data agreement. The developed model in this study had a strong correlation of $R^2 = 0.92$. The adj. R^2 was 0.83, indicating an acceptable compromise. The standard deviation (S.D.) of 0.95 was smaller than the mean value (3.15), indicating a strong correlation between anticipated and actual model data. Fig. 6 shows the projected model's good performance. The projected model's relevance is shown by the figure's straight line of expected and actual values.

4.4.3. Analysis of variables correlation using 3D-graphs

The response surfaces shown in Fig. 7 demonstrate the effects of crack position and MSMA wire position with respect to magnet position on the change in magnetic flux percentage of concrete following exposure to crack in the structural beam. The X and Y-axis correspond to the explanatory variables, whilst the Z-axis corresponds to the dependent variable. Upon examination of the data, it is evident that the highest values of change in magnetic flux are attained at the MSMA wire position of 15 mm from the magnet and a distance of around 13 mm between the magnet and the crack tip. In contrast, the concrete exhibits the lowest magnetic flux change when subjected to a 45 mm depth of MSMA wire from the magnet and a 70 mm distance of crack from the magnet.

4.4.4. Optimisation of parameters

The optimised values of D1 and D2 were obtained through the RSM optimisation tool. D1 and D2 were selected in range, and output was selected as optimised. The output-optimised solution is shown in Fig. 8(a–c). The maximum change in magnetic flux of 9.51 % is obtained at an 8.50 mm crack distance from the magnet and 17.5 mm depth of MSMA wire from the surface of the beam.

4.5. ANN modelling outputs

4.5.1. ANN model training and validation

The ANN model does not require any specific experiment design. It understands the correlation between inputs and outputs through neuron interactions. The ANN modelling training, validation, and testing results are shown in Fig. 9(a–d). The optimal number of

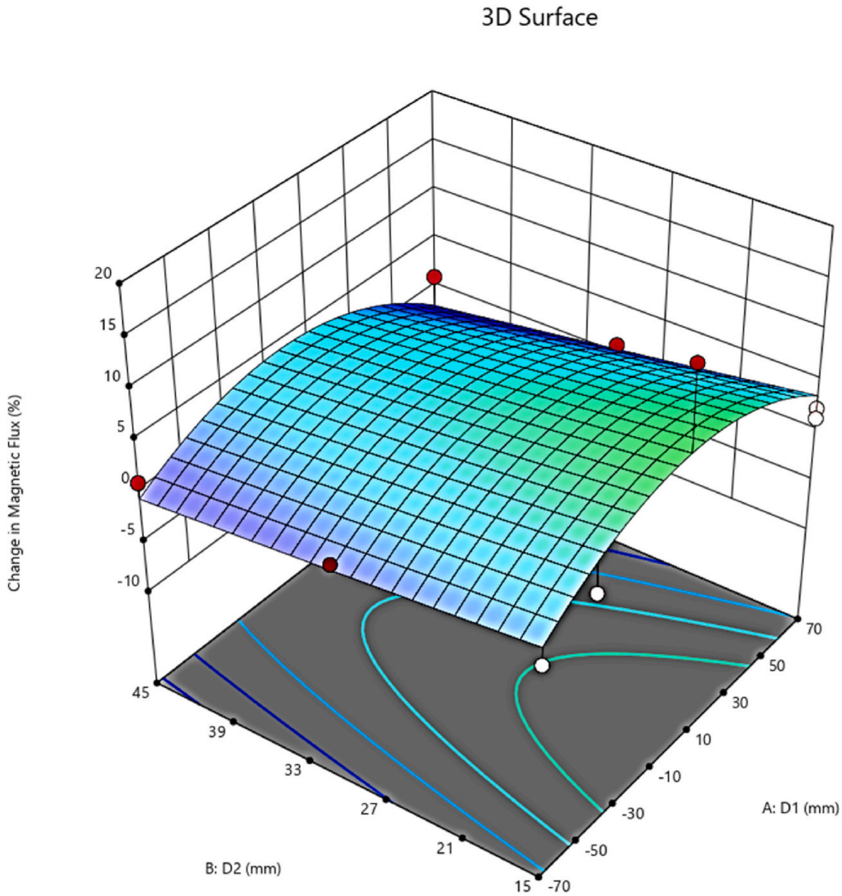

Fig. 7. 3D plot for interaction of variables D1, D2 and output change in magnetic flux.

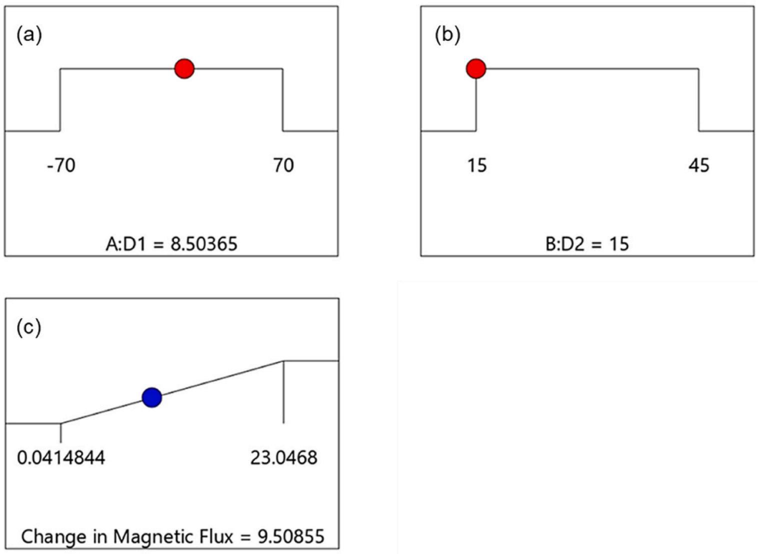

Fig. 8. Ramp solution of outcomes including (a) input A = D1, (b) input B = D2, and (c) output = change in magnetic flux.

neurons obtained was 12. The suitable training algorithm was Levenberg Marquardt. The model was evaluated based on MSE and R-value.

The model's training efficiency was 0.967. The developed ANN model was validated, giving an R-value of 0.99. The ANN model training, validation, and testing parameters are given in Table 3. The results show that ANN can be successfully used to determine the change in magnetic flux at various MSMA wire and crack positions.

4.5.2. ANN model application for prediction

The trained ANN model was used to estimate the change in magnetic flux over a range of larger beam dimensions. The results are given in Fig. 10(a and b). The results in Fig. 10(a) show that with the current magnet and MSMA wire diameter, the change in magnetic flux reduces to almost zero at an axial distance of 100 mm from the magnet to the crack. Also, the magnetic flux reduces to zero at a wire position of about 100 mm distance from the surface, as shown in Fig. 10(b). Hence for the detection of cracks in larger beams, larger magnets and larger wire diameters would be needed. Also, multiple magnets may help in the detection, if posted at regular intervals, or a change in magnetic flux won't be detected.

5. Discussion

The study determined the magnetic flux density in damaged structures using a permanent magnet, sensor and MSMA wire. The change in magnetic flux density due to internal damage is determined by a local region of SIM in MSMA wire. The relative distances between the magnet, sensor, and reinforcing wire remain constant, and only changes in computed magnetic flux density are due to local phase transformations in the MSMA wire. The results showed that magnetic flux density reduced while increasing the distance between the magnet and wire; also, the flux was reduced while increasing the axial distance between the magnet and crack tip.

To understand the relationship between the parameters, the data was modelled using RSM and ANN to adopt the change in magnetic flux while changing the wire distance from the surface of the concrete beam and changing the crack position. The RSM analysis showed that the change in magnetic flux was highly dependent on the MSMA and crack position. A larger change in magnetic flux was observed in close proximity of wire and crack to the permanent magnet. This higher change in magnetic flux denotes the crack presence in the concrete beam. The ANN was successfully trained and validated with a lower MSE of 3.034 and 0.59, respectively. The R-value was 0.97 and 0.99 for training and validation, respectively. The model was tested as well for the 15 % dataset. The R-value for testing was 0.99. It showed that ANN was capable of understanding the correlations between variables. The ANN model was successfully employed to predict the magnetic flux while changing the wire position in the beam or crack position in the beam. The findings helped to automate the magnetic sensing system. It also provided an insight towards the size and location selection for a MSMA wire for magnetic sensing. The developed model can be applied for various beam sizes to find the best possible magnet and wire position to predict the crack presence with the aid of developed magnetic flux. The findings of the study are relevant to experiments conducted on a small scale in a laboratory setting. Additional efforts are required to enhance the data-collecting system for experiments conducted in real-time. Larger datasets can enhance the modelling accuracy. In this study 27 dataset points were used for ANN modelling. This dataset is enough to prove the validity of the model in the magnetic sensing field. Many studies have used 22 or 20 data points to model the ANN [34,35]. The results suggest that magnetic sensing using MSMA can be effectively used for SHM of concrete.

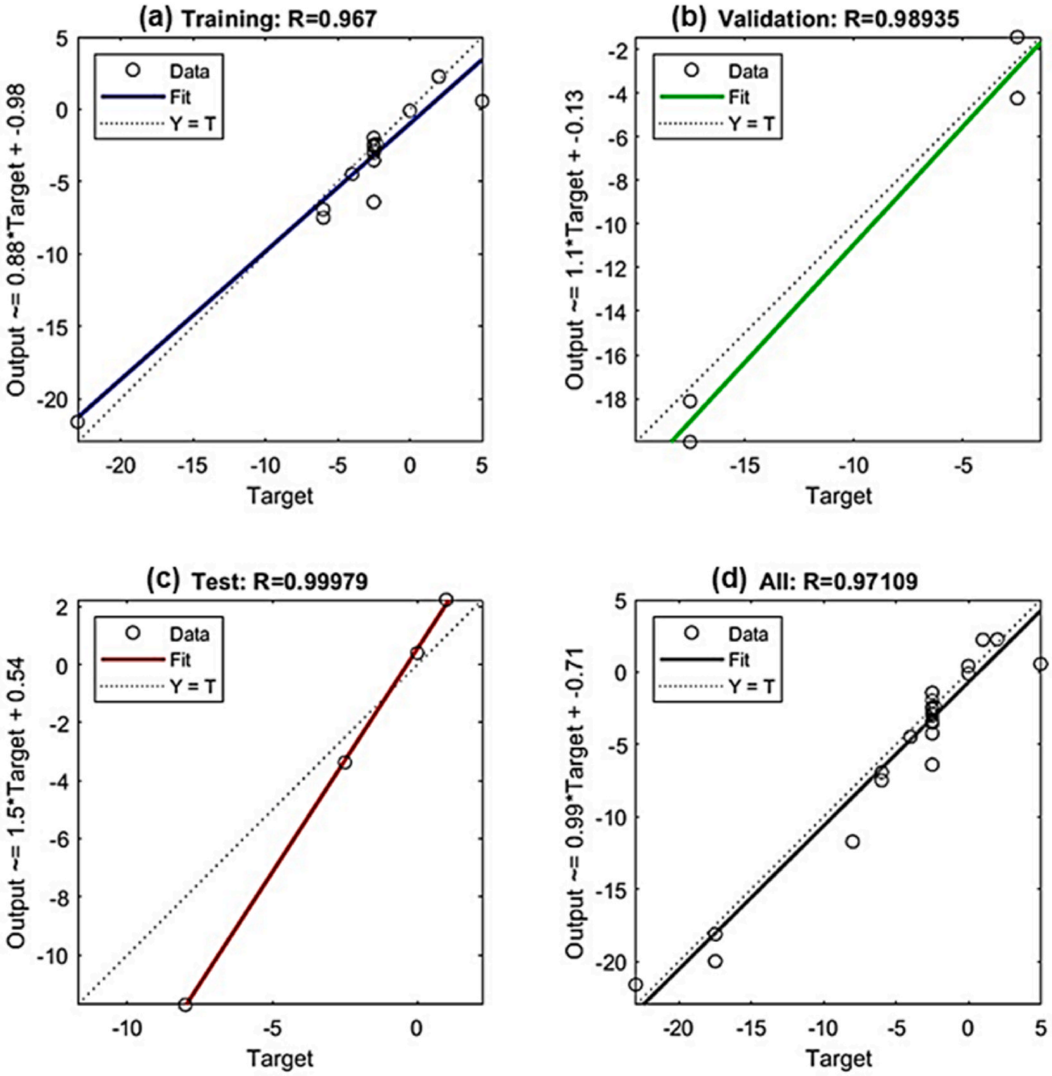

Fig. 9. ANN modelling plots for (a) training, (b) validation, (c) testing, and (d) overall training states.

Table 3
Parameters of ANN model.

	Observation	MSE	R
Training	19	3.034	0.97
Validation	4	0.5999	0.99
Test	4	7.8067	0.99

The study also suggested that RSM and ANN are simple, cheaper and easy-to-apply methods for the modelling, prediction and optimisation of process parameters. The models needed less complex data to understand the data trend. The learning rate of models was quick. Various models have been reported in concrete structure prediction problems. Such as [36] reported a thick-walled cylinder model for analysing the sea-sand concrete cover cracking. The predicted outputs showed an error of up to 10 % in comparison to experimental results. The proposed model was complex, time-consuming, needed large amounts of data and required deep expertise compared to the models reported in this study, viz., RSM and ANN. There are no studies that have applied RSM and ANN in magnetic sensing of cracks in concrete. Few studies that applied RSM and ANN were focused on the detection of various other parameters of concrete. Such as applied RSM to predict the durability of concrete pavements [37]. The model performed well. In another study hybrid deep neural network-horse herd optimisation model outperformed the RSM in optimizing the mechanical characteristics of concrete [38]. A prediction model based on Random Forest feature selection and Grey Wolf algorithm optimised support vector regression was reported for the bond strength measurement of concrete [39]. An extensive data was needed for the models. A modified

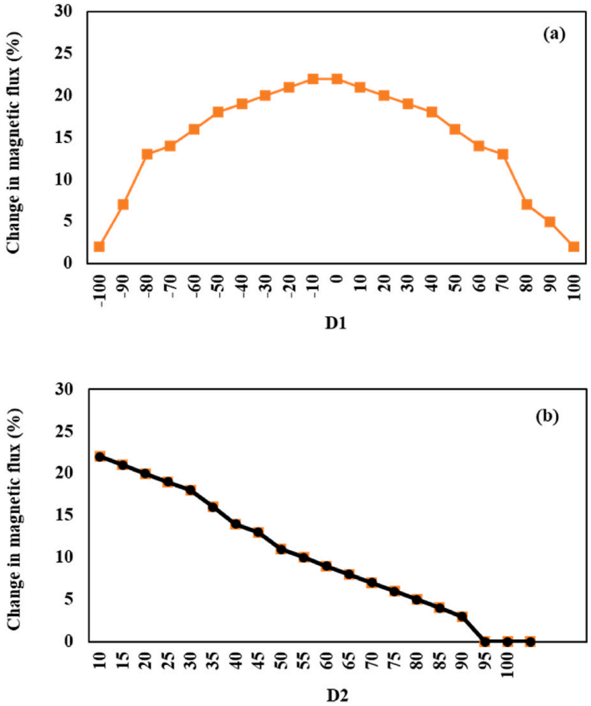

Fig. 10. ANN model prediction results: (a) Change in magnetic flux with changing D1 and (b) Change in magnetic flux with changing D2.

cracked membrane model was applied to modify the mechanical calculation model for the detection of concrete crack widths [40]. The model performed very well for 101 dataset testing. The reported data showed the gap in the literature that is addressed in the current study. The models reported in this study are simple, easy to understand, reliable, require less data and quick to apply. However, few limitations that may be expected from the models are that they are highly data dependant and the performance may vary by varying the dataset. Therefore, careful consideration should be given to data collection when applying the RSM and ANN models.

6. Conclusion

This paper presents an investigation of the use of MSMA reinforcing wires for SHM of concrete for internal crack detection. The work established the RSM and ANN models to predict the change in generated magnetic flux of a concrete structure containing an embedded MSMA wire, following exposure to a fracture in the structure. The models were developed using empirical data derived from prior investigations. The input data for the model included the position of the crack and the placement of the MSMA wire, while the output data consisted of the corresponding percentage change in magnetic flux. The main aim of the work was to provide a model based on RSM and ANN for predicting the alteration in magnetic flux after being exposed to fractures in a concrete-MSMA composite structure. The results suggested that MSMA wire position, wire size and crack position played an important role in the magnetic sensing capability of MSMA wires. Both developed models were less time-consuming and showed high accuracy. The non-destructive evaluation of cracks using computational methods is a recent topic of interest and current study contributed to it well. Further, investigations must be made for larger beams and complex reinforcements using the same methods or advanced hybrid models. The study opened the doors for future research in structural health monitoring using magnetic sensing. Also, the accuracy of ANN can be improved in future studies using larger datasets.

Data availability statement

The data reported in this study has not been deposited into a publicly available repository. The data has been included in the article or supplementary material or referenced in the article.

CRediT authorship contribution statement

Hifsa Khurshid: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bashar S. Mohammed:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Naraindas Bheel:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Willy Anugrah Cahyadi:** Writing – review & editing, Project administration, Funding acquisition. **Husneni Mukhtar:** Writing – review & editing, Project administration, Funding acquisition.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used QuillBot and Grammarly service in order to paraphrase and grammar corrections of the manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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