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ORIGINAL ARTICLE

Application of fuzzy cognitive maps for crack categorization in columns of reinforced concrete structures

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Abstract The detection of damage at an early stage that affects the supporting element of civil structures proves to be very significant to save invaluable human life and valuable possessions. In this research work, the severity of cracks in the supporting column is assessed using a new technique. This piece of research study uses the soft computing method of fuzzy cognitive map (FCM) to model the domain experts' knowledge and the knowledge assimilated through relevant literature to grade the severity of cracks in supporting column. The FCM grading model is further improved by using the Hebbian learning algorithms. The presented work demonstrates the classification and prediction capabilities of FCM for the respective structural health monitoring application, using two well-known and efficient FCM learning approaches viz. nonlinear Hebbian learning (NHL) and data-driven nonlinear Hebbian learning (DD-NHL). The proposed crack severity grading model classifies the cracks in supporting column into three categories, namely fine crack, moderate crack and severe crack. The proposed model uses DD-NHL algorithm. DD-NHL is trained with 70 records and tested with 30 records and gives an overall classification accuracy of 96 %. The obtained results are better compared to other popular machine learning-based classifiers. The proposed method helps even the non-experts to find the possible causes of crack and reports them to structural engineers, to start maintenance in an appropriate stage, using various crack control techniques. Also, a software tool for crack categorization was developed based on the FCM method and its learning capabilities. Thus, it is easier for the users/civil engineers to use this software to make decisions in civil engineering domain and improve their knowledge about the health of the structure.

Keywords Structural health monitoring · Fuzzy logic · Fuzzy cognitive map · Crack categorization · Hebbian learning · Data-driven nonlinear Hebbian learning

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1 Introduction

Structural health monitoring (SHM) is a process for providing precise and timely information about the physical condition of civil structures. SHM is emerging as an essential tool to help structural engineers to improve the protection and maintainability of civil structures. SHM improves safety and functionality of structures and provides a timely warning of expected failures. Cracks occur in structural elements when the stress of a part increases more than its strength [7]. The stress could be caused by outwardly applied forces such as dead, live, wind loads foundation settlement or could be induced inside due to thermal movements, moisture changes, chemical action, etc. Figure 1 shows some sample images of cracks occurrence in columns.

Cracks in buildings can be classified either as structural or non-structural cracks. Structural cracks result from incorrect design, faulty construction or overloading and may cause danger to the safety of the building [7]. Non-structural cracks result from internal stress of building materials which do not cause any threat to the safety of buildings [7]. Cracks which occur in supporting column belong to structural crack category. The structural element designed to support compression loads is termed as column. Columns support vertical loads from the floor and roof slabs and transfer these loads to the footings. Since failure of column often causes widespread destruction, columns are designed with a higher reason of safety than beams.

Diagnosis of cracks was performed by various organizations [1, 10]. However, these methods were not helpful for non-experts who perform regular inspection of cracks. A fuzzy-based pattern recognition model [4] was proposed for crack diagnosis along with cause and effect diagram. The model was applied to three different forms like slab surface, walls and columns. But this method was focused on diagnosing only the possible causes of crack. A fuzzy-based system for the assessment of the state of the buildings was proposed in [14]. The assessment focuses on the state of building history, environmental conditions, structural capacity and durability. The limitation of the above work was that it considered fixed values for assessment criteria which are not similar for all the building regions. Fuzzy set theory was used by [15] which helped non-experts to diagnose crack causes. However, this method did not provide information about whether the crack occurred due to a single cause or multiple causes. Rough set theory for the diagnosis of crack in concrete structures was proposed by [13]. The causes of the cracks were classified based on the crack characteristics like time of formation and shape.

All the related works discussed above were used primarily for the categorization of crack causes. Also, domain experts' knowledge was not employed for crack cause categorization. As it comes from our knowledge, the proposed work is the first of its kind to use fuzzy cognitive map (FCM) to model domain experts' knowledge together with the data collected from reliable structural tests for predicting the severity level of cracks occurring in the supporting columns. The main reason to employ the FCM for crack modeling and severity grading is their abilities for modeling and analyzing complex systems. FCM consists of state variables connected by links that indicate the causal relationships in contrast to the mathematical and statistical approaches which have difficulty to accomplish this task [16]. FCM is usually created by human experts who design it based on the knowledge gained through experience at different circumstances. Human knowledge and experience prove to be valuable for the selection of concepts and determination of weights between the interconnected concepts devoted to the structured FCM. The main advantage of FCM is its ability to integrate and adapt human knowledge [28]. FCM has been used for knowledge representation [31], fault detection [22], process control [9], data mining in Internet [17] and medical decision support system [25, 31]. A two-level integrated FCM model was used in tumor grading and breast cancer risk prediction [11]. In the field of precision agriculture, FCM has been used for categorizing the coconut yield level for the given set of agro-climatic conditions [12].

The use of FCM for structural damage detection was initiated by [3] for detecting structural damage in a cantilever beam from measured frequencies. This work was

Fig. 1 Cracks in columns

motivated by the above cited work of [3], focusing on analyzing the possible mechanical, thermal and chemical causes for cracks occurring in the supporting columns. Also it concentrates on grading the severity level of cracks occurring in the supporting columns.

The proposed method uses FCM for crack diagnosis in the supporting element column. The various causes influencing the severity of cracks are analyzed using FCM modeling features, and the cracks are categorized into three grades, namely fine crack, moderate crack and severe crack. As cracks with a width of more than 0.3 mm cause durability problems [6], they have to be attended promptly; thus, crack categorization plays a crucial role in SHM. The objectives of the proposed work are to: (1) investigate the effectiveness of fuzzy cognitive maps for the reported SHM application, (2) develop a soft computing-based crack diagnosis expert system using FCM to help non-experts to diagnose the causes of crack and its severity level and (3) analyze the influence of various chemical, mechanical and thermal agents on the development of cracks and its prognosis.

This paper is structured in the following way: Sect. 2 summarizes the main aspects of the FCM construction using expert knowledge. Section 3 explains the FCM modeling process for crack categorization. Section 4 explains the details of the evaluation of FCM grading model and gives a comparison with other existing techniques. Section 5 discusses the results, and Sect. 6 concludes the paper by citing the advantages and limitations of the proposed method.

2 Fuzzy cognitive maps

2.1 Overview of FCM

FCM is a soft computing technique that follows a reasoning approach similar to the human reasoning and human decision-making process [16]. FCM is constructed using nodes and edges among them. Nodes represent the concepts in the problem domain. Concepts denote the attributes and states of the system. The interconnection between the concepts, also known as weighted link, represents the cause and effect relationship that a concept has on others. The causal relationships among the concepts are illustrated by either positive or negative values. In a positive relationship, an increase or decrease in the cause variable causes the effect variable to move in the same direction. In a negative relationship, the cause concept causes the effect concept to move in opposite direction. Concepts take values in the range [0, 1], while weights of the edges take values in the range [−1, 1].

After drawing the FCM, a diagram to matrix transformation takes place representing the weights. There are two general groups of methods for constructing the weight matrix [23]. These are the expert knowledge methods and the historical data methods. In the first group, the expert knowledge is used to generate the important factors and interrelationships. In the second group, the historical data are used to extract the interrelationships between concepts. A comparative study on different learning techniques for FCM can be found in [23] and [26].

An $N \times N$ matrix is formed where N is the number of concepts used in FCM. Each entry at row i, column j represents the degree to which the ith concept influences the jth concept along with the sign. In the absence of causal relation between any pair of concept, a zero value in the (i, j) place of matrix is defined. Once the FCM has been created, it should be initialized. Each concept C_i represents one of the key factors of the modeled system. Let the value assumed by C_i be A_i. Initial weights are based on the available experts' perceptions about the possible casual associations between the cause–effect nodes. The experts' perceptions are collected in the form of linguistic variables like positively high, positively low, negatively high and negatively low. Next, these perceptions are aggregated using the SUM method and the overall linguistic weight is defuzzified with the center of gravity (CoG) method [32] to produce the respective numeric value in the range [−1 1]. The numerical weight is represented as W_{ij}. In a similar way, all the weights of FCM are calculated and the weight matrix is constructed. When the FCM is initialized, it interacts freely until it:

1. Reaches a fixed equilibrium.
2. Exhibits a limit cycle behavior.
3. Exhibits a Chaotic behavior.

The FCM converges after several cycles. Among the above-listed situations, the fixed equilibrium state is the most valuable compared to others.

2.2 Learning in FCM

Learning in FCM involves updating the weights among the concepts of an FCM model. A learning strategy helps the development of the FCMs by fine-tuning their initial weights. This can be succeeded by applying training algorithms like that of artificial neural networks [21, 22]. Learning algorithms help on overcoming the gaps found in expert knowledge and make the system converge in the desired regions so as to get more acceptable classification and inference capabilities.

Hebb-based learning FCM models are very effective for solving complex problems with small and incomplete data sets [19]. The main drawback of Hebb-based learning methods is that their strength and accuracy depend purely on the expert knowledge which in turn decreases the efficiency of the model. The more the number of nodes, the more complex the model building becomes. In addition, often no expert is available for building the FCM model. The NHL [27] is a learning algorithm of this type which learns from initial expert-developed FCM model, and a set of conditions are imposed on output concepts.

In the second group, historical data are used to learn the FCM model comprising concept values at successive points in time. Learning FCM by using historical data means finding a connection matrix where successive FCM decision-making iterations provide concept values as close as possible to the historical data. The evolutionary algorithms [29, 34] have proven to be seen as fast and robust methods for learning an FCM model; however, they use historical data for learning FCM and they are out of scope in this study. DD-NHL [33] which is an extension to NHL uses historical data to improve the quality of learned FCM model and does not rely on initial, expert-based developed FCM when compared to the generic NHL method. The DD-NHL method [33] produces better FCM models based on their quality when compared to those developed by using the generic NHL method.

2.3 FCM learning using Hebbian learning algorithm

The Hebbian learning rule is one of the oldest learning rules that specify how much the weight of the interconnection between two concepts is to be adjusted in proportion to the product of their activation. In NHL algorithm, the concepts in FCM can be triggered synchronously in each iteration step using Eq. (1). In each iteration step, the weights W_{ij} (weight from ith concept to jth concept) are updated using Eq. (3) and these modified weights and concept values are used in the next iteration.

$$A_i^{(k)} = f\left(A_i^{(k-1)} + \sum_{\substack{j \neq 1 \\ j=1}}^{N} A_j^{(k-1)} \times W_{ji}^{(k-1)}\right) \tag{1}$$

In the above equation, $A_i^{(k)}$ is the value of concept i in kth iteration. $W_{ji}^{(k-1)}$ is the weight from jth concept to the ith concept in iteration step $(k-1)$. f is the sigmoid threshold function and is calculated as given in Eq. (2).

$$f = \frac{1}{1 + e^{-\lambda x}} \tag{2}$$

where λ determines the steepness and is a positive value, assumed as 1 in the proposed work. The learning rule which used in this model is given in Eq. (3). This equation is used in each iteration step to update the weight matrix.

$$W_{ji}^{(k)} = W_{ji}^{(k-1)} + \eta_k A_j \left(A_i^{(k)} - A_j W_{ji}^{(k-1)}\right) \tag{3}$$

where $W_{ji}^{(k)}$ is the updated weight in kth iteration. η_k is the learning parameter value in kth iteration, which is a small positive value. In NHL algorithm, the weights of the concepts with no relations that have zero values and only the nonzero weights in the weight matrix are updated. The values of the concepts are updated till all the concepts converge at their desired region. The termination conditions of the algorithm are represented in Eqs. (4) and (5), which utilize the information on desired values of the output concept which has predefined range of values.

$$F1 = \sqrt{\sum_{i=1}^{N} (\mathrm{DC}_i - T_i)^2} \tag{4}$$

$$F2 = \left|\mathrm{DC}_i^{(k)} - \mathrm{DC}_i^{(k-1)}\right| < e \tag{5}$$

where DC represents decision concept, T_i is the desired target value of the decision concept, and e is the tolerance level in the magnitude of the difference in DC in two successive iterations. Normally e is assumed as a very small positive value like 0.001. If the learning process is repeated indefinitely without convergence, then the iteration process needs to be stopped and the model requires reconstruction with the help of experts' knowledge. The maximum number of iterations is generally set to a high value like 500, and if the iterations go beyond this level without convergence, then the model needs to be reconstructed so that it would be able to converge in the preferred region.

In DD-NHL algorithm, the historical data are considered for learning of FCM. The historical data form a matrix D, where d_{ij} corresponds to the ith concepts value at jth time point. The difference between NHL and DD-NHL [33] algorithms lies in concept value calculation. In NHL, Eq. (1) is used for concept value updating, whereas in the case of DD-NHL, in each iteration, the next row of matrix D is considered as the new concept value. So, the matrix updating is carried out based on the historical data. If the termination condition is not reached, we start using the same data points again, i.e., the first row of matrix D.

3 FCM modeling process for crack categorization

The SHM process is a complex one, consisting of different factors and many possible interrelations among them [8]. Based on the expert knowledge in the field of structural engineering, the factors which are influencing the occurrence of cracks in column were identified. These factors are crucial for the prediction of severity of cracks. A team of domain experts' was pooled to find these factors and their relationships. Eleven factors were identified by domain experts as influencing factors listed as (C1–C11) in

Table 1. These are the factors that stimulate the crack occurrence. The C12 is defined as the output/decision concept that predicts the grade of the crack and can be called *Fine crack, Moderate crack* and *Severe crack*.

The range of values for the above-listed factors complies with the IS 456-2000 (Indian Standard, Plain and Reinforced Concrete; Code of Practice) standards. The reported work is under standard loading conditions of column [19, 20]. The column load (P_u) is calculated using Eq. (6) given below for short axially loaded member type.

$$P_u = 0.4f_{ck} * A_c + 0.67f_y * A_{sc} \tag{6}$$

where P_u = axial load on the member, f_{ck} = characteristic compressive strength, A_c = area of concrete, f_y = characteristic strength of the compression reinforcement, and A_{sc} = area of longitudinal reinforcement for columns

The causal relationships between the factors listed in Table 1 are subjectively defined by the domain experts using linguistic terms and always in accordance with the recommendations and guidelines available in [6]. Even though the experts' suggestions agree with the recommendations and guidelines (as given in [6]) in a macro-context, the subtle variations on their subjective opinions about the influence of each concept on the decision concept should be properly captured and precisely modeled at the stage of system designing. This is well accomplished by FCM's inherent ability to aggregate the subjective opinions about the causal interactions of the participating elements. The weights of the edges of the interconnected concepts are determined by aggregating the linguistic causal associations assigned by several experts. In the proposed system, three domain experts, namely a structural engineer, a structural engineering researcher and a technical cite supervisor, were involved in deciding the concepts and the weight interconnections among the concepts. The weights were determined by the domain experts in terms of linguistic expressions and later aggregated using CoG method [32]. Wherever possible, the domain experts followed the IS 456-2000 standards in deciding the causal associations between the various influencing factors. For instance, the influence between some of the factors selected for building the FCM can be found in [6]. Some of them are:

- Cracks cause corrosion of reinforcement (as per the guidelines in Sect. 2).
- Cracks occur due to load and thermal variation (as per the guidelines in Sect. 2.2).
- Thickness of cover strongly influences cracks (as per Sect. 2.3.1 of [6]).
- High water–cement ratio increases crack occurrence (as per Appendix 2.1 of [6]).
- The lesser the cover, the more the crack occurrence (as per Appendix 2.1 of [6]).
- If the chloride value exceeds the permissible value, it will lead to crack development (as per Appendix 2.1 of [6]).
- Shrinkage and thermal movement, which are due to design deficiency, if not considered will lead to crack (as per Appendix 2.1 of [6]).

Complementing the available literature, the domain experts linguistically described the strength of causal associations between each pair of concepts. Subsequently, the calculation of the weight of the edge connecting a pair of concepts is described below.

Let us consider the interconnection between column load (C2) and crack width (C12) for illustration. The three experts stated their opinions to decide the weight as follows:

Table 1 Main features influencing cracks in columns

Concepts	Range of values	Clause number in IS 456-2000 standard[b]
C1: eccentricity	Normal ($\leq$20 mm), high (>20 mm)	25.4
C2: column load	Normal ($>P_u^a$), low ($<P_u^a$)	39.3
C3: thickness of cover	Low (<40 mm), normal (=40 mm)	26.4.2.1
C4: water cement ratio	Normal (=0.55), high (>0.55)	As per expert opinion
C5: corrosion of reinforcement	Absent (0–0.4), present (0.3–0.7), intense (0.5–1)	As per expert opinion
C6: shrinkage	Absent (0–0.4), present (0.3–0.7), intense (0.5–1)	As per expert opinion
C7: spacing of bars	Normal ($\leq$300 mm), high (>300 mm)	26.5.1.3
C8: crazing	Absent (0.1–0.6), present (0.5–1)	As per expert opinion
C9: temperature changes	Normal (=300 °C), high (>300 °C)	As per expert opinion
C10: thermal movement	Absent (0.1–0.6), present (0.5–1)	As per expert opinion
C11: chloride attack	Normal (0.6 kg m^{-3})	Table 7 of 8.2.5.2
C12: crack	Fine, moderate, severe	As per expert opinion

[a] P_u is calculated as discussed in Eq. (6) given below

[b] Wherever possible, the valid range of concept values is fixed as per standard guidelines; in case of absence of standards, experts were asked to fix ranges

3.1 First expert

If a small change in value of concept C2 occurs, then a large change in value of concept C12 is caused.

Inference The influence from C2 to C12 is *positively high*.

3.2 Second expert

If a very small change in value of concept C2 occurs, then a large change in C12 is caused.

Inference The influence from C2 to C12 is *positively very high*.

3.3 Third expert

If a very small change in the value of concept C2 occurs, then a medium change in the value of the concept C12 is caused.

Inference The influence from C2 to C12 is *positively high*.

The three linguistic variables inferred from the domain experts are summed up, and an overall linguistic weight is produced. With the defuzzification method of CoG, the weight is transformed into the numerical value 0.70 in the range [−1, 1].

The 11 identified concepts (Table 1) keep relations with each other, to characterize the process of predicting the severity of cracks in the column. The prediction gives the level of the severity of cracks to the structural engineer, who plans the healing of column crack using standard crack control method.

Using the same approach as described above, weights between each pair of relationship are calculated and the weight matrix W is produced. This weight matrix W is used in the simulation process of FCMs, constituting an essential part in the inference process. Figure 2 illustrates the constructed FCM model for predicting the severity of crack with the numerical value of weights.

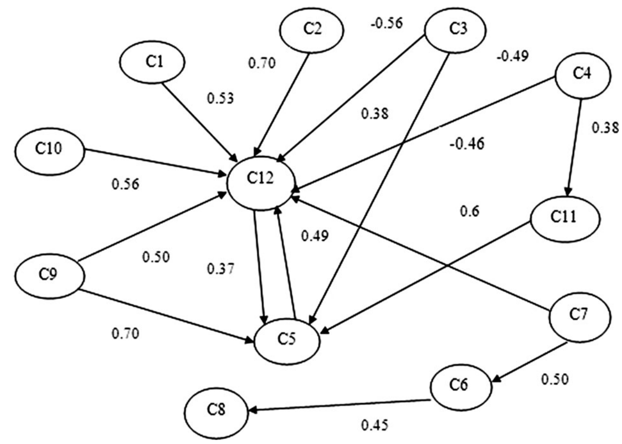

Fig. 2 The FCM model for crack categorization

4 Evaluation of FCM grading model

4.1 FCM learning using DD-NHL

In order to classify the cracks, a classification algorithm based on the FCM learning approach of DD-NHL was implemented. This learning approach was selected due to the availability of a relatively small data set after the initial FCM construction by experts' knowledge.

The historical data set consists of 100 records which are used for training, testing and later for classifying the crack into three classes. The categorization of the crack is based on the width of the crack [7] as: Fine crack is the one with less than 1 mm in width; moderate crack has width between 1 mm and 2 mm, and the crack larger than 2 mm width is considered as severe crack as per expert recommendations. The corresponding values are normalized using the formula given in Eq. (7)

$$X_{\text{normalized}} = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})} \tag{7}$$

For example, the crack width of 2.3 mm is normalized as 0.8, assuming that the most crack width occurring is 2.7 mm and the least crack width is 0.5 mm in the provided historical data set. After normalization, the ranges have been assigned as: $0.1 \leq$ fine ≤ 0.19, $0.2 \leq$ moderate ≤ 0.69 and $0.7 \leq$ severe ≤ 1.

The historical records were used for both learning and testing by the DD-NHL algorithm. Seventy samples out of 100 input samples were considered to be used for training, and the 30 remaining samples were considered for testing. For each algorithm performance, there is a random selection of these cases for training and testing. During each run, the classification accuracy is calculated by the testing cases. The overall classification accuracy is estimated by the mean value of the calculated classification accuracies produced after a large number of experiments.

Based on the DD-NHL, the proposed classification algorithm consists of the following steps:

Input For a system with N concepts and K data points, the input data form a matrix $D = [d_{ti}]$, where d_{ti} corresponds to the value of ith concept ($i = 1, \ldots, N$) at the tth pattern, where $t = 1, \ldots, K$ (K is the number of records), with size $K \times N$, which is called input data matrix. Each row of the given matrix, illustrated as $A(t) = [A1(t), A2(t),\ldots An(t)]$ where $t = 1, \ldots, K$, stores values of activations of the concepts at the tth iteration.

In the learning phase, the algorithm has to find the decision boundaries that partition the underlying output vector from step one into three sets, one for each class. For this purpose, one-dimensional decision boundaries were determined by using the least Euclidean distance method [5]. The FCM model is learned using Eq. (1) through Eq. (3) till the termination condition in Eq. (4) is reached. The learning rate was set as 0.001. After reaching the termination state, the produced weight matrix is used for testing the remaining 30 cases referring to the category of the crack.

Next, in the testing phase, the remaining 30 cases of the sample records following the steps of DD-NHL were classified using the previously produced decision boundaries at each experiment which were used to estimate the classification accuracy. Thus, for a total number of 70 experiments, the mean classifier accuracy was estimated. The result of classification for the concept C12 in the convergence region by the FCM model is depicted in Fig. 3. The decision line separates the grades into three categories. Grade values <0.51 show fine crack cases, while the values between 0.51 and 0.56 are considered as moderate cracks. Values >0.56 are categorized as severe crack cases. The overall classification accuracy of the proposed method is 96 %.

A comparative analysis was made to compare the classification accuracy of DD-NHL with other benchmark machine learning classifiers. Four machine learning algorithms namely Naïve Bayes, multilayer perceptron, J48 and Bayes net were used for testing using WEKA Tool [18].

As shown in Table 2, the proposed DD-NHL-FCM grading model gives diagnostic output with very high accuracy. A classification accuracy of 100 % (5/5) was achieved for fine grade, 87 % (7/8) of the records were graded as moderate cases, and 100 % (17/17) of the remaining ones were graded as severe cases. The results in Table 2 prove that FCM is able to give crack diagnosis with a degree of accuracy higher than the well-known classification engines.

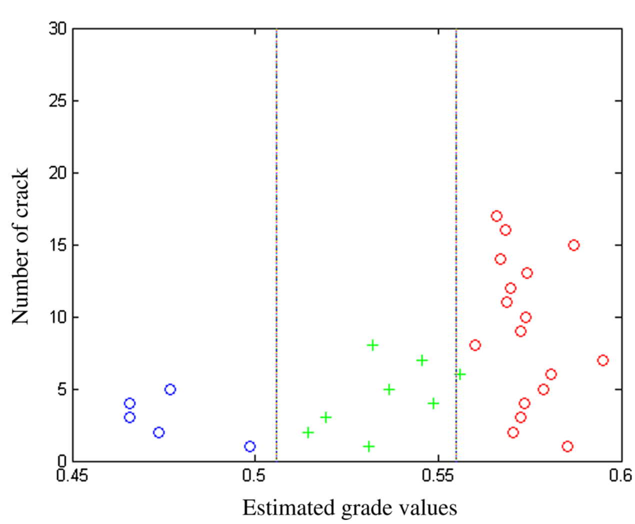

Fig. 3 Categorization of cracks

4.2 FCM learning using NHL

This section discusses the applicability of NHL-FCM to infer the knowledge about categorization in supporting column without using earlier historical data for training and testing as in the earlier case of DD-NHL-FCM of Sect. 4.1. For this purpose, the unsupervised learning of FCM using NHL rule is adopted on the proposed FCM model given in Fig. 2. The NHL algorithm is used to reinforce the initial causal weights assigned by the group of experts to get the desired mapping between input and output [2]. The unsupervised learning of FCM for crack categorization is tested using different scenarios as illustrated below.

4.2.1 Scenario A: influence of column load on crack severity

Column load is one of the mechanical agents which are considered by the domain experts as a strong influential parameter affecting the occurrence of crack in columns. Thus, an increase in column load is highly likely to cause a severe crack. To test the above-mentioned fact using NHL, a scenario with increased column load was formulated where the values of other parameters were assumed to fall within their normal limits. The input vector is defined as follows. The range of values for each factor is given in Table 1. If the value of a factor considered as input is within its normal range, then this factor will not be considered as a factor affecting the crack occurrence. If the input factor takes values other than the normal range, it will be a factor that induces crack. Based on this, the input values are chosen for all the factors affecting the crack occurrence.

Eccentricity is 20 mm, column load is 0.9, thickness of cover is 40 mm, water–cement ratio is 0.55, corrosion is 0.3, shrinkage is 0.3, spacing of bars is 300 mm, crazing is 0.1, temperature change is 300 °C, thermal movement is 0.2, and chloride attack is 0.6 kg m^{-3}.

The values given in the input vector are experimental values. These input values need to be normalized in the 0–1 scale, using Eq. (7) in order to be used in FCM simulation process. For example, the temperature value of 300 °C is normalized to the value 0.5000, assuming that the maximum temperature value $X_{\max}$ is 303 °C and the minimum temperature value $X_{\min}$ is 297 °C. Similarly, all other concept values are normalized. After normalizing the above values, the input vector is formed as:

Table 2 Comparison of different classifiers using confusion matrix

Classifier	Crack class	Severe	Moderate	Fine	Classification accuracy (%)
DD-NHL-FCM	Severe	17	1	0	96 (29/30)
	Moderate	0	7	0	
	Fine	0	0	5	
Multilayer perceptron	Severe	13	0	0	86 (26/30)
	Moderate	0	5	3	
	Fine	0	1	8	
Bayes net	Severe	7	0	6	70 (21/30)
	Moderate	0	5	3	
	Fine	0	0	9	
Naïve Bayes	Severe	13	0	0	80 (24/30)
	Moderate	0	6	2	
	Fine	3	1	5	
J48	Severe	13	0	0	76.6 (23/30)
	Moderate	1	5	2	
	Fine	4	0	5	

$$A^{\mathrm{init}-1} = [0.0000 \quad 0.9000 \quad 1.0000 \quad 0.5500 \quad 0.3000 \quad 0.3000 \quad 0.0000 \quad 0.1000 \quad 0.5000 \quad 0.2000 \quad 0.6000 \quad 0]$$

The concepts and weights are learned using Eq. (1) through Eq. (3) till they converge to a steady state, according to the termination criteria in Eqs. (4) and (5). The learning rate was set initially to 0.1 and decreased exponentially at each iteration k as:

$$\eta^{(k)} = \frac{\eta^{(k-1)}}{(2k+1)} \tag{8}$$

The concepts reach the steady state after 10 iterations, and the values of concepts are:

$$A^{\mathrm{final}-1} = [0.6590 \quad 0.6590 \quad 0.6590 \quad 0.6590 \quad 0.8612 \quad 0.7480 \quad 0.6590 \quad 0.7503 \quad 0.6590 \quad 0.6590 \quad 0.7305 \quad 0.9869]$$

The value of DC (C12) converges at 0.9869 after 10 iterations. The value above 0.7 is considered as severe crack by the experts. Therefore, the final result obtained corresponds to the severe crack.

4.2.2 *Scenario B: influence of chemical attack on crack severity*

Chloride attack is one of the chemical agents that are believed by the experts to moderately influence the occurrence of crack in column. Thus, an increase in chloride value is likely to cause a moderate crack. To test the above-mentioned fact, using NHL, a scenario with increased chloride value was formulated where the values of the other parameters were assumed to be within their normal limits. The initial values of factors for this scenario are given below: Eccentricity is 20 mm, column load is 0.1, thickness of cover is 40 mm, water–cement ratio 0.5, corrosion is 0.1, shrinkage is 0.2, spacing of bars is 300 mm, crazing is 0.1, temperature change is 300 °C, thermal movement is 0.2, and chloride attack is 0.66 k gm^{-3}.

After normalizing the above values using Eq. (7), the input vector is formed as:

$$A^{\mathrm{init}-1} = [0.0000 \quad 0.1000 \quad 1.0000 \quad 0.500 \quad 0.1000 \quad 0.2000 \quad 0.0000 \quad 0.1000 \quad 0.5000 \quad 0.2000 \quad 0.6600 \quad 0]$$

The concepts and weights are learned using Eq. (1) through Eq. (3) till they converge to a steady state or equilibrium point according to the termination criteria in Eq. (4) and Eq. (5). The concepts reach the steady state after 10 iterations, and the values of concepts are:

$$A^{\mathrm{final}-1} = [0.5590 \quad 0.6590 \quad 0.5490 \quad 0.4690 \quad 0.3322 \quad 0.3320 \quad 0.4590 \quad 0.5513 \quad 0.4523 \quad 0.5469 \quad 0.5305 \quad 0.5242]$$

The value of DC (C12) converges at 0.5242 after 10 iterations. The DC values between 0.2 and 0.69 are considered as moderate crack decisions by the experts. Therefore, the final result obtained corresponds to the moderate crack.

4.2.3 *Scenario C: influence of thermal agents on crack severity*

According to the experts' recommendations, thermal agents have a mild influence on the occurrence of crack. To study the effect of thermal agent on the severity of crack, the following values of input factors were considered as input values to the proposed system: Eccentricity is 20 mm, column load is 0.1, thickness of cover is 40 mm, water–cement ratio 0.5, corrosion is 0.1, shrinkage is 0.2, spacing of bars is 300 mm, crazing (0.2), temperature change is 300 °C, thermal movement is 0.8, and chloride attack is 0.6 kg m^{-3}.

After normalizing the above values using Eq. (7), the input vector is formed as:

$$A^{\text{init}-1} = [0.0000 \quad 0.1000 \quad 1.0000 \quad 0.500 \quad 0.1000 \quad 0.2000 \quad 0.0000 \quad 0.2000 \quad 0.5000 \quad 0.8000 \quad 0.6000 \quad 0]$$

The concepts and weights are learned using Eq. (1) through Eq. (3) till they converge to a steady state according to the termination criteria in Eq. (4) and Eq. (5). The concepts reach the steady state after 10 iterations, and the values of concepts are:

$$A^{\text{init}-1} = [0.1290 \quad 0.3790 \quad 1.3590 \quad 0.4590 \quad 0.4322 \quad 0.7320 \quad 0.5590 \quad 0.4513 \quad 0.6523 \quad 0.6459 \quad 0.6305 \quad 0.0312]$$

The value of DC (C12) converges to 0.1312 after 10 iterations. The values between 0.1 and 0.2 are considered as fine crack decisions by the experts. Therefore, the final result obtained corresponds to the fine crack.

A user-friendly decision support tool has been designed for predicting the severity of crack for the given set of mechanical, chemical and thermal agents. This software is functional and is available for structural engineers. The details of the software are given in the next subsection.

4.3 Description of suggested GUI

Crack categorization software has been developed for this study intending to provide the structural engineers with a front-end decision support tool for estimating the level of crack for the given set of factors which influence the occurrence of crack. The tool helps even the non-experts to find the causes of crack and report the results to structural engineers, so as to start maintenance in an appropriate stage. The user interface of the crack categorization software, developed for the purpose of this study, asks experts to define the values of each concept and predicts the crack severity level for the given set of factors by invoking the proposed NHL-FCM model.

5 Results and discussion

The proposed work is focused on crack categorization using DD-NHL-FCM and NHL. The DD-NHL-FCM gives 96 % classification accuracy which is superior to the other computational intelligence-based methods as shown in Table 2. The real strength of DD-NHL-FCM is that it is capable of learning even from a small data set as it is built over domain experts' knowledge, while other machine learning algorithms like multilayer perception and back propagation network are very much dependent on a large data set to be used for training. Additionally, they need many epochs to converge (which means to reach a decision). Hence, FCM approach enhanced with the DD-NHL learning algorithm is superior over the other machine learning algorithms in terms of (1) smaller training set required for learning and (2) faster convergence.

The inference ability of NHL learning algorithm was used for testing new knowledge. From the various case studies conducted, it was observed that the NHL algorithm produces expected result in concurrence with the expert opinions. The main reason that we used Hebbian learning algorithm for FCM in this study is the availability of domain knowledge from experts which is used for the initial FCM construction. Usually, when the data set is relatively small for learning (small number of historical records), the DD-NHL algorithm is selected for FCM learning, thus to change the initial structure providing better modeling and system performance.

Furthermore, we have not selected genetic or evolutionary learning algorithms for FCM reconstruction, due to the specific type and number of available historical data. More specifically, the DD-NHL-FCM is capable of learning even from a small data set as the FCM is initially built over domain experts' knowledge, while the other evolutionary FCM learning algorithms need a relatively large data set of historical data to be used for FCM training. Previous studies have also shown the suitability of this type of learning when small data sets are available [24].

Moreover, evolutionary algorithms need an objective function (maximization or minimization function) to be defined and the performance of these algorithms in determining the best weights largely depends on how well the objective function is defined. The higher computational complexity involved in these algorithms is justified only when there is no expert knowledge available to decide the weights. As FCMs are constructed on the basis of domain expertise, the DD-NHL algorithm acts upon the initial weights defined by the experts to further refine them and thus to fill the gaps in the expert knowledge with the help of the available historical data. Nevertheless, a future extension of the presented work is planned by utilizing the evolutionary algorithms to experiment whether these algorithms give a higher accuracy than what is obtained in the current work.

The main limitation of the FCM model is its dependence on expert knowledge to deduce the causal relationships. Besides, FCM becomes unstable and gives unpredictable results if the causal weights are not properly assigned.

In summary, this work mainly elaborates the development of the knowledge-based system using FCM modeling approach for crack categorization in civil structures as well as the development of a software tool for supporting civil engineers in predicting the crack severity. We selected to develop a software tool with an easy-to-use GUI for structural engineers (end users) to give them a front-end decision support tool for estimating the category of crack for the given set of interrelated parameters.

6 Conclusion

The purpose of the proposed work was to introduce and highlight the capabilities of FCM as a promising tool for crack modeling and categorization in SHM. The novelty of the proposed approach is not on the theory of FCM method but on the application domain on a new case study of civil engineering of crack prediction in SHM. The efficient NHL-based algorithm for FCM learning has been used for crack categorization, providing better results than other machine learning algorithms. The ability of FCM based on the DD-NHL method has shown high accuracy. The proposed DD-NHL-FCM uses historical data for classification. DD-NHL method helps even the non-experts to find the possible causes of crack and reports them to structural engineers, to start maintenance in an appropriate stage, using various crack control techniques. Also, the NHL for FCM is used for scenario testing and analysis, helping on the decision support capabilities of the proposed tool. Moreover, a software tool for crack categorization was developed based on the FCM method and its learning capabilities. Thus, it is easier for the users/civil engineers to use this software to make decisions in civil engineering domain and improve their knowledge through the provided results of SHM. Also, the proposed model is an easily interpretable and transparent soft computing tool and is useful even for naive users.

The proposed method agrees much with the way an expert makes a perceptive classification based on his/her accumulated experience. In future, the DD-NHL-FCM model application could be investigated for crack diagnosis in other structural elements like slabs and beams. The proposed work can also be extended for diagnosing the flexural crack and shear cracks in structural members which are also complex problems.

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