Fuzzy Inference System as a Tool for Management of Concrete Bridges

Amir Tarighat
Civil Engineering Department, Shahid Rajaee Teacher Training University
Iran

1. Introduction

Bridges are important infrastructures all over the world. We have invested and spent a lot of money in constructing them. Also we assign big budgets for their maintenance, repair and strengthening annually. Since the number of bridges is increasing the amount of money needed to preserve the existing bridges at minimum standard level is considerable. In order to make decision for optimal budgeting we should know how bridges respond to various kinds of deteriorating factors and what their current and future conditions will be.

Why bridges need maintenance, repair and strengthening depend on many factors. Deterioration of bridges is due to aging, material deterioration under environmental conditions, increasing traffic volume and higher weights of vehicles. There are many factors which are responsible to make decision what the current condition and/or rating of a bridge is. Practically to make logical and defendable decisions the main action is to inspect bridges. Inspection provides a lot of collected data that should be stored and retrieved at any required time to obtain useful and practical information regarding the bridge condition and its immediate need. At this stage and by appropriate information in hand it can be possible to predict the remaining service lives of bridges.

Bridges are susceptible to many defects during their service lives. The main common defects that occur on cast-in-place concrete slab (deck) bridges include: cracking, scaling, delamination, spalling, efflorescence, honeycombs, pop-outs, wear, collision damage, abrasion, overload damage, reinforcing steel corrosion (Chen & Duan, 2000; Hartle et al., 2002). These defects are symptoms showing some kinds of deteriorations. Inspectors should report these symptoms and consequently type of deterioration(s) should be diagnosed.

Inspecting a concrete bridge deck includes visual and advanced inspection methods. The inspection of concrete bridge deck for symptoms like cracks, spallings, and other defects is primarily a visual activity. However, hammers and chain drags can be used to detect areas of delamination. In addition, several advanced techniques are available for concrete bridge deck inspection. Nondestructive methods include: acoustic wave sonic/ultrasonic velocity measurements, electrical methods, electromagnetic methods, rebound and penetration methods, carbonation and so many others if needed (Hartle et al., 2002).

Visual inspection is the primary method used to evaluate the condition of the majority of the existing bridges. Visual inspection is a subjective assessment and it may have a significant

impact on the diagnosis and decisions to be made. For example a defect reported from one inspector may be different from the others. In order to overcome this unwilling fact nondestructive testing methods have been suggested for objective inspection in recent decades. Although these methods are more accurate than visual inspection, there are some kinds of problems. Interpretation of their results needs experience together with the knowledge about deteriorations of bridge material and damage types of its elements. Therefore results of visual inspection and some nondestructive testing methods are inherently uncertain and vague. It is to notify that the linguistically describing results are more uncertain and vague. Degree of uncertainty and level of vagueness depend on many parameters such as inspector's experience, definition of symptom or deterioration type, level of defect categorizations and many others.

Among many methods it seems that models based on artificial intelligence which apply soft computing methods are more attractive for dealing with uncertain and vague data in managing bridges. Fuzzy Inference System (FIS) is capable of being used in areas for decision making when data is uncertain. One of the most attractive advantages of FIS is its tolerability to noisy (uncertain and vague) data.

Based on the type of problems with uncertain and vague data, different FIS modeling types can be regarded as appropriate and easy methods for managing bridges (Tarighat & Miyamoto, 2009).

After introduction section this chapter continues with section 2 and its subsections showing the need for managing bridges and introduces Bridge Management System and Bridge Health Monitoring system. Ambiguity in diagnosis and decision making based on the collected data in above mentioned systems are discussed in section 3. Section 4 explains why fuzzy inference systems are suitable in managing systems. Its subsections are about fuzzy inference systems including Mamdani's method and Adaptive Neuro Fuzzy Inference System (ANFIS) method. Then some case studies and some typical applications of fuzzy inference system for managing bridges are included in section 5. Section 6 concludes this chapter.

2. Managing bridges

All the inspection data should be stored in inventory and inspection databases and they should be used to get information for what to do in the next step of managing bridges. Therefore a kind of managing system is required to use the data and making appropriate and logical decisions for further actions.

2.1 Bridge Management System

Bridge Management System (BMS) has great roles in managing bridges. The main feed into any BMS is inspection data. It is designed to provide information not easily available from available data. BMS can provide the following:

- Improvements in the type and quality of data that is collected, stored, managed, and used in a bridge system analysis
- A logical method for setting priorities for current needs
- Realistic and reliable forecasts of future needs
- Ways to implement changes in management philosophies and goals

It is obvious that how and to what extents the above mentioned items can be fulfilled by the available data.

In general, the condition of a BMS element is identified by condition states and corresponding condition state language. Each element has a range of minimum to maximum condition states. Information from each BMS element along with expert input to predict how the condition of that element will change over time is used in BMS computer programs. BMS programs can estimate future network funding levels based on the predicted future bridge conditions and the corresponding costs to repair or replace them (Washington State Bridge Inspection Manual, 2010).

The following outline provides a short BMS summary for a typical inspection:

- Identify the BMS elements that apply to the structure.
- Determine the total quantity for each element.
- Inspect bridge and record the deficient quantity for each element in the corresponding condition state.

2.2 Bridge Health Monitoring System

Generally in advanced BMS there is a module named Bridge Health Monitoring System (BHMS). BHMS can be considered as one of the most important parts of a practical BMS.

In bridge structures there are many different unforeseen conditions that we do not have enough information about them. Although in design codes we are forced to consider some parameters or factors affecting structural behavior there are even more items that we cannot consider them practically. Therefore it is probable to have some risk for not fulfilling the complete standards of safety. Presently health and performance are described based on subjective indices which are not precise. In addition there are some possibilities for unobserved and undiscovered symptoms, deteriorations, and damages in bridge structures due to limited or no accessibility to some elements. The immediate consequence is that the real health index is not that thought and considered. This unwilling fact impacts the effectiveness and reliability of any managerial decision irrespective of sophistication in the management process. Moreover, even experienced engineers may find visual signs of defects, deterioration and damage and cannot be able to diagnose the causative mechanisms, or their impact on the reliability of the bridge and its global health. The global health of a bridge as a whole system, inclusive of the performance criteria corresponding to each limit states is actually what is needed for effective managerial decisions. There are needs of periodic inspections to detect deterioration resulting from normal operation and environmental attack or inspections following extreme events, such as earthquakes or hurricanes. To quantify these system performance measures requires some means to monitor and evaluate the integrity of bridge structures while in service (Wang & Zong, 2002). BHMS can help managers to know about the healthiness of a bridge at any given time.

BHMS may also have other applications. For example any damage in some elements of a bridge has direct effect on its load bearing capacity especially vibration characteristics. In other words this effect can change the overall behavior of the bridge under loads which cause the bridge to vibrate. Based on this fact any method for damage detection which is

capable of showing the location and severity of damage can be considered useful for bridge maintenance and repair departments (Haritos, 2000).

Bridge real time monitoring during service provides information on structural behavior under predicted loads, and also registers the effects of unpredicted overloading. Data obtained by monitoring is useful for damage detection, safety evaluation, and determination of the residual load bearing capacity of bridges. Early damage detection is particularly important because it leads to appropriate and timely interventions. If the damage is not detected, it continues to propagate and the bridge no longer guarantees required performance levels. Late detection of damage results in either very elevated refurbishment costs or, in some cases, the bridge has to be closed and dismantled. In seismic areas the importance of monitoring is more critical. Subsequent auscultation of a bridge structure that has not been monitored during its construction can serve as a basis for prediction of its present and future structural behavior. Based on these facts there are many applications for developing BHMS. As mentioned one of the most important applications of BHMS is damage detection. Among the attractive methods for damage detection problems are models based on artificial intelligence especially soft computing methods (Ou et al., 2006; Wu & Abe, 2003).

As it is used several times in above paragraphs, health can be defined as the reliability of a bridge structure to perform adequately for the required functionalities (Aktan et al., 2002). Some of these functionalities are:

- Utility
- Serviceability and durability
- Safety and stability of failure at ultimate limit states
- Safety at conditional limit states

It is not possible to quantify health and reliability of a bridge system for many of the limit states without extensive data that we often do not have. Based on a general definition monitoring is the frequent or continuous observation or measurement of structural conditions or actions (Wenzel & Tanaka, 2006). There is another definition which gives more detail: structural health monitoring is the use of in-situ, non-destructive sensing and analysis of structural characteristics, including the structural response, for detecting changes that may indicate damage or degradation [Housner & Bergman, 1997). Fig. 1 shows basic components of a typical BMS and BHMS.

In summary BMS and BHMS are used to:

- Structural management
- Increase of safety
- Knowledge improvement
- Rating the current condition of bridge or its components
- Predicting the remaining service life
- Structural/system identification
- Damage detection/diagnosis and damage localization
- Forced vibration-based damage detection
- Wind induced vibration-based damage detection
- Ambient vibration-based damage detection

- Remote sensing and wireless sensor networks
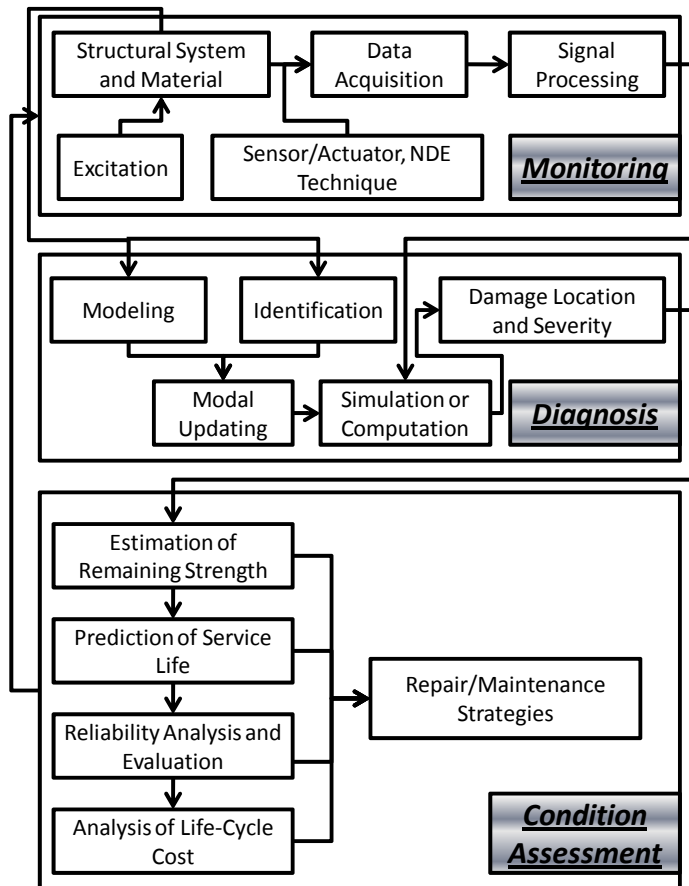- Life cycle performance design

Fig. 1. Basic components of a typical BMS and BHMS

3. Ambiguity in diagnosis and decision making

Recently it is become obvious that although BMS and BHMS can be precisely used for managerial issues but there is an important fact about the collected data. Data is not perfect. It is found that the results and data-driven interpretations are prone to some degree of vagueness. Therefore, the obtained data that should be altered to information has inherently some degrees of uncertainty and vagueness (Tarighat & Miyamoto, 2009).

In managing a bridge we are concerned about condition state or standard level of a requirement. For example we want to know what the current condition state of a bridge is and to how it has been deviated from the previous and known condition state (Washington State Bridge Inspection Manual, 2010).

In most cases diagnosis is necessary to make decision for next action to return to a standard bridge condition state. Whenever we are going to diagnose, it is common to have circumstances in which we must make decision via ambiguous data and information. Practical diagnosis in managing bridges is the making of judgments about a bridge's condition state or damage detection using expert knowledge, but the observation of symptoms includes results of visual inspection and non destructive testing methods, bridge's history, and the circumstances of the diagnosis. For example, if we think about diagnosis during a regular inspection versus before a repairing operation, indications of possible deterioration or damage and need for retesting are important in the former, but in the latter, importance is placed on certainty rather than possibility. Normally a repairing operation is not performed without confirmation of the existence of deterioration or damage in the affected element of a bridge.

The words we use concerning symptoms often contain expressions of frequency and probability, such as *sever cracks* or *high corrosion*. In contrast to this kind of linguistic ambiguity, ambiguous circumstances exist in the distinguishing of the symptom, such as different inspectors' reporting differing symptoms.

When thinking about the ambiguity that originates in the characteristics discussed above, we must also consider the ambiguity that arises from the participation of experts in the bridge evaluation. In general, there is a large dependence on visual inspection results, which are subjective judgments. Since visual inspection is cheaper, faster and sometimes simpler than other inspecting methods it is more probable to have more ambiguity levels in data and interpretations (Terano et al., 1992).

Here are some more detailed explanations of the ambiguity in managing bridges. Condition rating is a judgment of a bridge component condition in comparison to its original as-built condition at a given time (Wang & Hu, 2006). Condition rating and damage detection are crucial methods and tools to conduct efficient maintenance and managing bridges. Condition rating indices are also useful for predicting future states which are completely time dependent. Based on the periodic inspections data at different time intervals deterioration rate of the material, elements and sometimes whole structure can be modeled. These models can be good tools for decision makers in future (Zadeh, 1976).

Related to condition rating definition there is another problem: what is the exact meaning of condition or health for material or bridge element in the structure? From practical point of view deterioration or damage symptoms should be easily distinguished. But in practice symptoms as signs of deteriorations cannot be easily distinguished and be reported or categorized in well-defined manner. Here, it becomes clear what the *subjective data* means. In other words the encoding of symptoms into condition rating is imprecise and involves *subjective judgments*.

Of greatest importance is the amount of variability found in the assignment of condition ratings at a given time. As an example results of the deck delamination survey conducted during some investigations indicate that this type of inspection does not consistently provide accurate results. In a case study the condition rating results analysis and the data revealed that the condition ratings were normally distributed. Table 1 shows the summary of statistical information from routine inspection for deck condition rating (Phares et al., 2000, 2001; Graybeal et al., 2001; Moore et al., 2001).

Bridge	Element	Average	Standard Deviation	Minimum	Maximum	Mode	N	Reference Rating
A	Deck	5.8	0.81	3	7	6	49	5
B	Deck	4.9	0.94	2	7	5	48	4
C	Deck	5.2	0.92	3	7	6	49	4
D	Deck	4.8	0.94	2	6	5	48	5
E	Deck	4.5	0.74	3	6	5	48	4
F	Deck	7.1	0.53	6	8	7	49	7
G	Deck	5.8	0.92	4	7	5	24	7

Table 1. Statistical information from routine inspection for deck condition rating (Phares et al., 2001).

The range of the results between min and max show the stochastic nature of the inspector's judgment. These stochastic representations show the fuzzy nature of the inspectors' judgments.

While current rating systems of concrete structures may give a fundamental understanding of structural deterioration conditions, their application is more or less limited in reflecting actual conditions. In some cases it is often difficult to cover complex structural behavior and environment in the real world. Uncertainties and fuzziness, along with complexity, add more difficulty to the estimation of condition rating by conventional methods. Therefore a better method may be a combination of logics and statistics. To take advantage of this approach in dealing with qualitative issues such as human factors, the influence of inspectors' judgment on structural condition rating and the effects of weather conditions on inspectors' judgment should be considered (Harris, 2006; Ma, 2006; Stephens, 2000; Wang et al., 2007; Yen & Langari, 1999).

Since the bridge inspection results are subjected to some degrees of imprecision and vagueness it is a good idea to use fuzzy set theory to overcome the shortcomings and problems of ordinary methods for prediction of condition of bridges. Fuzzy information or fuzzy data can be encountered in managing bridges. The main reasons for fuzzy data are imprecision in measured data and subjective judgments.

Knowledge engineering methods for dealing with uncertainty in many aspects of condition prediction are used to produce expert systems. Expert systems are expected to be effective for ill-defined problems (problems in which it is either difficult or impossible to define a method of approach).

In most cases, either the clear knowledge of ill-defined problems cannot be obtained, or completion of the knowledge set must be approached gradually. In other words, there are many cases in which knowledge is *ambiguous*. Meaning of the word *ambiguous* is also ambiguous and vague. Just as knowledge must be formulated and written down for a user to understand it, ambiguity must take some form before it can be dealt with technically. Therefore, ambiguity that is dealt with in knowledge engineering is classified and written down as follows:

- Nondeterminism
- Multiple meanings
- Uncertainty

- Incompleteness
- Fuzziness or imprecision

Uncertainty and fuzziness have a particularly close relationship with each other and systems that handle knowledge with fuzziness have been created even in the field of knowledge engineering (Terano et al., 1992).

One of the best ways of dealing with this kind of problems is the application of fuzzy inference system. Fuzzy inference system is capable of dealing with imprecise, imperfect, uncertain and vague data and information. Thus, it can be good candidate toward development of practical BMS and BHMS.

A measure of imprecision is advantageous for symptoms representation. Uncertainty characterizes a relation between symptoms and deteriorations/damages, while imprecision is associated with the symptoms representation.

4. Fuzzy inference systems and managing bridges

Fuzzy logic is an interesting and easy-to-use method for practical inference problems in engineering. It relates significance and precision to each other very well. Fuzzy logic-based inference systems enable the use of engineering judgment, experience and scarce field data to translate the level of deterioration or damage to condition rating (Rajani et al., 2006).

One of the best methods to deal with decision making problems such as condition rating of bridges is application of Fuzzy Inference System (FIS). In order to diagnose deterioration type or damage detection in concrete bridges and to increase accuracy and errors reduction caused by subjective human judgment fuzzy inferring is the appropriate choice (Wang & Hu 2006). Fuzzy sets can be used for modeling uncertainty of detection and imprecision of symptoms.

Detection support systems operate on rules with fuzzy premises, which represent imprecise symptoms. During inference fuzzy relations or implications are used, so conclusions are also represented in the form of fuzzy sets (Straszecka, 2006).

4.1 Fuzzy inference system

System modeling based on conventional mathematical tools (e.g., differential equations) is not well suited for dealing with ill-defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy *if-then* rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. A Fuzzy Inference System (FIS) is a way of mapping an input space to an output space using fuzzy logic. A FIS tries to formalize the reasoning process of human language by means of fuzzy logic (that is, by building fuzzy IF-THEN rules). This *fuzzy modeling* or *fuzzy identification*, first explored systematically by Takagi and Sugeno, has found numerous practical applications in control different engineering application and fields.

Fuzzy if-then rules or *fuzzy conditional statements* are expressions of the form *IF A THEN B*, where A and B are labels of *fuzzy sets* characterized by appropriate membership functions. Due to their concise form, fuzzy if-then rules are often employed to capture the imprecise

modes of reasoning that play an essential role in the human ability to make decisions in an environment of uncertainty and imprecision.

Another form of fuzzy if-then rule has fuzzy sets involved only in the premise part. By using Takagi and Sugeno's fuzzy if-then rule, we can use a relationship among variables or simply a formula. However, the consequent part is described by a nonfuzzy equation of the input variable.

Both types of fuzzy if-then rules have been used extensively in both modeling and control. Through the use of linguistic labels and membership functions, a fuzzy if-then rule can easily capture the spirit of a "rule of thumb" used by humans. From another angle, due to the qualifiers on the premise parts, each fuzzy if-then rule can be viewed as a local description of the system under consideration. Fuzzy if-then rules form a core part of the fuzzy inference system. Fig. 2 shows the general form of a Fuzzy Inference System (FIS) (Jang, 1993).
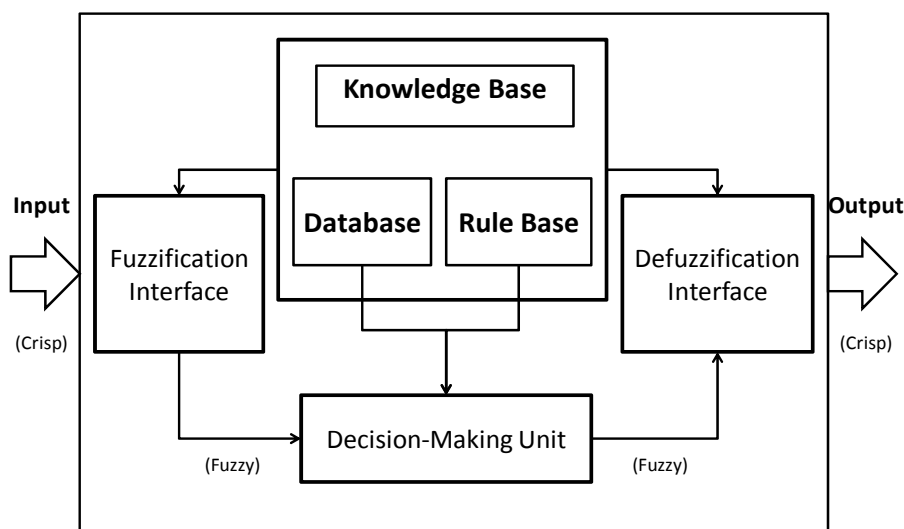

Fig. 2. Fuzzy Inference System (FIS)

4.1.1 Mamdani's method

Mamdani's method is the most commonly used in applications, due to its simple structure fuzzy calculations. This method as a simple FIS method is used to solve almost general decision making problems for practical issues.

Let X be the universe of discourse and its elements be denoted as x. In the fuzzy theory, fuzzy set A of universe X is defined by function $\mu_A(x)$ called the membership function of set.

$$m_A(x): X \in [0,1] \text{, where } \mu_A(x) = 1 \text{ if } x \text{ is totally in } A;$$
$$\mu_A(x) = 0 \text{ if } x \text{ is not in } A;$$
$$0 < \mu_A(x) < 1 \text{ if } x \text{ is partly in } A.$$

This set allows a continuum of possible choices. For any element x of universe X, membership function $\mu_A(x)$ equals the degree to which x is an element of set A. This degree, a value between 0 and 1, represents the degree of membership, also called membership value, of element x in set A. Any universe of discourse consists of some sets describing some attributes to the output. The main idea of fuzzy set theory is dealing with linguistic variables (Tarighat & Miyamoto, 2009).

A linguistic variable is a fuzzy variable. For example, the statement "a is b" implies that the linguistic variable a takes the linguistic value b. In fuzzy systems, linguistic variables are used in fuzzy rules. The range of possible values of a linguistic variable represents the universe of discourse of that variable. A fuzzy rule can be defined as a conditional statement in the form:

IF (x is a) THEN (y is b)

where x and y are linguistic variables; and a and b are linguistic values determined by fuzzy sets on the universe of discourses X and Y, respectively. The main and most important characteristic of fuzzy systems is that fuzzy rules relate fuzzy sets to each other. Fuzzy sets provide the basis for output estimation model. The model is based on relationships among some fuzzy input parameters (Baldwin, 1981).

All these definitions and arrangements are used to infer output based on the inputs. The most commonly used fuzzy inference technique is the so-called Mamdani method. Mamdani method is widely accepted for capturing expert knowledge. It allows describing the expertise in more intuitive, more human-like manner. However, Mamdani-type fuzzy inference entails a substantial computational burden.

The Mamdani-style fuzzy inference process is performed in four steps:

Step 1.   Fuzzification of the input variables

The first step is to take the crisp inputs, $x1$ and $y1$, and determine the degree to which these inputs belong to each of the appropriate fuzzy sets.

Step 2.   Rule evaluation

The second step is to take the fuzzified inputs and apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator *(AND or OR)* is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function. Now the result of the antecedent evaluation can be applied to the membership function of the consequent. The most common method of correlating the rule consequent with the truth value of the rule antecedent is to cut the consequent membership function at the level of the antecedent truth.

Step 3.   Aggregation of the rule outputs

Aggregation is the process of unification of the outputs of all rules. We take the membership functions of all rule consequents previously found and combine them into a single fuzzy set.

The input of the aggregation process is the list of found consequent membership functions, and the output is one fuzzy set for each output variable.

Step 4. Defuzzification

The last step in the fuzzy inference process is defuzzification. Fuzziness helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp number.

The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number (Esragh & Mamdani, 1981).

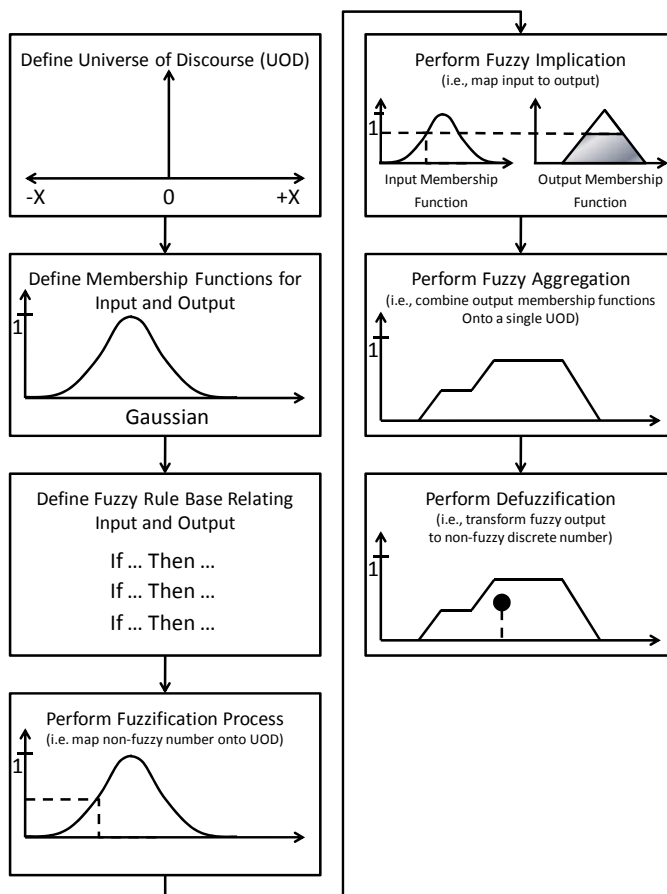Fig. 3 depicts the flowchart for fuzzy logic analysis based on Mamdani's fuzzy inference method (Symans & Kelly, 1999).

Fig. 3. Flowchart for fuzzy logic analysis based on Mamdani's fuzzy inference method (Symans & Kelly, 1999)

4.1.2 Adaptive Neuro Fuzzy Inference System (ANFIS) method

Adaptive Neuro Fuzzy Inference System (ANFIS) is a multilayer feed-forward network which uses neural network learning algorithms and fuzzy reasoning to map inputs into an

output. It is a fuzzy inference system implemented in the framework of adaptive neural networks.

In order to explain ANFIS a fuzzy inference system with two inputs x and y and one output z is considered (Jang et al., 1997). In a first-order Sugeno fuzzy model with two fuzzy if-then rules we have:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$

Fig. 4 shows the reasoning procedure for the considered Sugeno model. Fig. 5 depicts the ANFIS architecture. As it is shown nodes of the same layer have similar functions. The output of the *ith* node in layer l is as $O_{l,i}$.

$$f_1 = p_1 x + q_1 y + r_1 \qquad f_2 = p_2 x + q_2 y + r_2 \qquad f = \frac{w_1.f_1 + w_2.f_2}{w_1 + w_2}$$
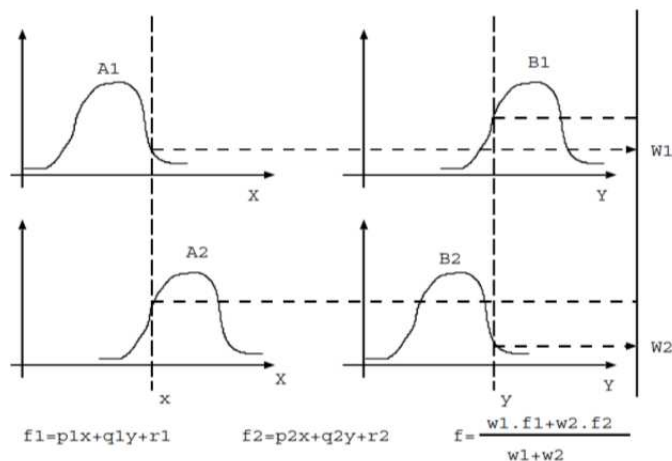
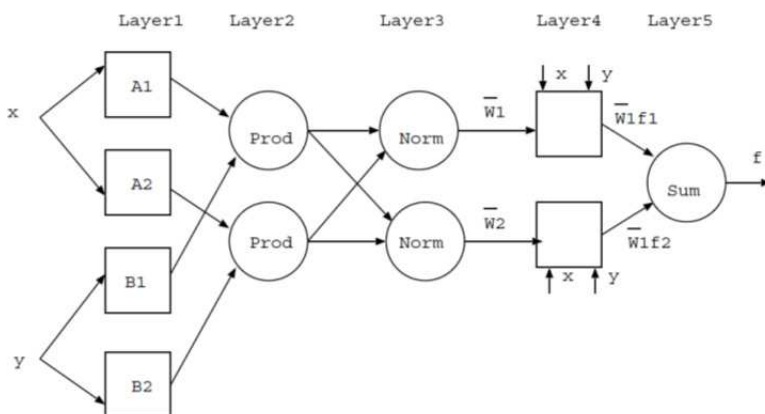Fig. 4. A two-input first-order Sugeno fuzzy model with two rules

Fig. 5. Equivalent ANFIS architecture

Following few paragraphs contain brief description of the different layers:

Layer 1: Every node i in this layer is an adaptive node with a node function:

$$O_{l,i}=\mu_{Ai}(x), \qquad \text{for } i=1, 2, \text{ or}$$
$$O_{l,i}=\mu_{Bi\text{-}2}(y), \qquad \text{for } i=3, 4 \tag{1}$$

where *x (or y)* is the input to node *i* and A_i *(or B_{i-2})* is an attribute associated with this node. In other words, $O_{l,i}$ is the membership grade of a fuzzy set *A (= A_1, A_2, B_1 or B_2)* and it specifies the degree to which the given input *x (or y)* satisfies the quantifier *A*. Here the membership function for *A* can be any appropriate parameterized membership function such as the generalized bell function:

$$\mu_A(x) = \frac{1}{1 + \left| \dfrac{x - c_i}{a_i} \right|^{2b_i}} \tag{2}$$

where *{ai, bi, ci}* is the premise parameters set. Changing the values of these parameters leads to change of the bell-shaped function. Therefore various forms of membership functions for fuzzy set *A* are possible.

Layer 2: Every node in this layer is a fixed node labeled Prod, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y), \; i = 1, 2 \tag{3}$$

Each node output represents the firing strength of a rule. In general, any other T-norm operators that perform fuzzy *AND* can be used as the node function in this layer.

Layer 3: Every node in this layer is a fixed node labeled Norm. The *ith* node calculates the ratio of the *ith* rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{4}$$

Outputs of this layer are called normalized firing strengths.

Layer 4: Every node *i* in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{5}$$

where $\overline{w}_i$ is a normalized firing strength from layer 3 and *{p_i, q_i, r_i}* is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: The only node of this layer is a fixed node labeled Sum, which computes the overall output as the summation of all incoming signals:

$$overall\;output = O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

It can be observed that the ANFIS architecture has two adaptive layers: Layers 1 and 4. Layer 1 has modifiable parameters *{ai,bi, ci}* and *{aj,bj, cj}* related to the input MFs. Layer 4 has modifiable parameters *{pij,qij, rij}* pertaining to the first-order polynomial. The task of the learning algorithm for this ANFIS architecture is to tune all the modifiable parameters to make the ANFIS output match the training data. Learning or adjusting these modifiable parameters is a two-step process, which is known as the hybrid learning algorithm. In the forward pass of the hybrid learning algorithm, the premise parameters are hold fixed, node outputs go forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the consequent parameters are held fixed, the error signals propagate backward and the premise parameters are updated by the gradient descent method. The detailed algorithm and mathematical background of the hybrid learning algorithm can be found in (Jang et al., 1997; Wang & Elhag, 2008).

The basic learning rule of ANFIS is the back propagation gradient descent, which calculates error signals (defined as the derivative of the squared error with respect to each node's output) recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the back-propagation learning rule used in the common feed-forward neural networks. From the ANFIS architecture in Fig. 5, it is observed that given the values of premise parameters, the overall output *f* can be expressed as a linear combination of the consequent parameters. On the basis of this observation, a hybrid-learning rule is employed here, which combines the gradient descent and the least-squares method to find a feasible set of antecedent and consequent parameters. The details of the hybrid rule are given in (Jang et al., 1997), where it is also claimed to be significantly faster than the classical back-propagation method.
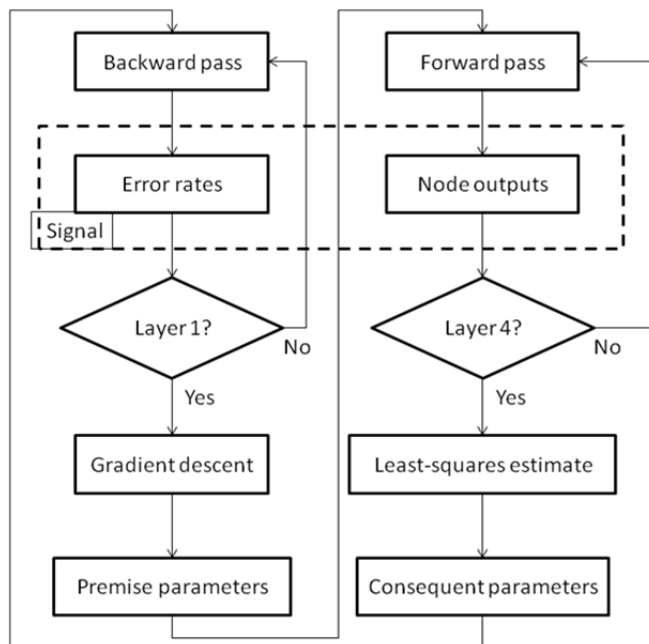

Fig. 6. Hybrid learning procedure of ANFIS

There are two passes in the hybrid-learning procedure for ANFIS. In the forward pass of the hybrid-learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least-squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent. When the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters

$$
\begin{aligned}
f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\
&= \overline{w}_1 (p_1 x + q_1 y + r_1) + \overline{w}_2 (p_2 x + q_2 y + r_2) \\
&= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2
\end{aligned} \tag{7}
$$

which is linear in the consequent parameters *p1, q1, r1, p2, q2, and r2* (Jang et al., 1997; Kandel & Langholz, 1993; Li et al., 2001; Sivanandam et al., 2007). A flowchart of hybrid learning procedure for ANFIS is shown schematically in Fig. 6 (Aydin et al., 2006).

5. Case studies and some typical applications of fuzzy inference system for managing bridges

As it is mentioned in earlier parts of this chapter and is shown in Fig. 1 the main concerns of bridge management systems are diagnosis of the encountered problems (deteriorations and/or damage detection) and finding the current condition of the bridge structure. It was also discussed that diagnosis and current condition determination accompany with ambiguity. In this section some case studies and applications are presented to show how fuzzy inference system can be used in bridge management issues.

5.1 A fuzzy system for concrete bridge damage diagnosis (DIASYN system)

Bridge management systems (BMSs) are being developed in recent years to assist various authorities on the decision making in various stages of bridge maintenance, which requires, first of all, appropriate preliminary deterioration diagnosis and modeling.

Diagnosis Synthesis (DIASYN) is a fuzzy rule-based inference system for bridge damage diagnosis and prediction which aims to provide bridge designers with valuable information about the impacts of design factors on bridge deterioration.

DIASYN is supposed to be a concept demonstration system for providing the bridge maintenance engineers and the bridge design engineers with assistance to obtain preliminary but important knowledge on individual bridge defects.

The DIASYN system incorporates a fuzzy reasoning process containing a rule base with its acquisition and update facility and a fuzzy inference engine with an explanation facility, and a user interface with option selecting capacity. Fuzzy logic is utilized to handle uncertainties and imprecision involved. The rules are if-then statements that describe associations between fuzzy parameters. Given the required input data, the inference engine evaluates the rules and generates an appropriate conclusion. Users can choose to make diagnoses of new cases or to update the rule base with new training data through the user interface.

The fuzzy rules provide associations between observed bridge conditions and damage causes. They are created by a rule generation algorithm that can convert crisp training data into fuzzy statements. The training data are collected from bridge inspection records and formalized into standard vectors. In the operational mode, the system reads a state vector of observed bridge condition and the inference engine performs damage cause implication through evaluation of the rules. The output of this implication procedure is a linguistic variable that describes the possible damage cause with a confident degree. This linguistic variable can be defuzzified by the explanation facility if a crisp output is desired. In the updating mode, new training vectors are input to generate new rules together with the existing training data. New rules, if any, will be installed in the rule base before the system gives a prompting of *updating finished* as output.

Inputs of DIASYN are:

- Design factors, i.e. structural type, span length, deck width, number of spans, wearing surface type, skew angle, etc.,
- Environmental factors, i.e. humidity and precipitation, climate region, traffic volume, temperature variations, etc.,
- Other factors, such as structure age, function class and location of damages.

The inference engine in DIASYN basically executes Mamdani's original reasoning procedure. The overall firing strength of the individual rule whose antecedents are connected with an *AND* operator, the intersection, is typically determined by taking the minimum value of the individual firing strengths of the antecedents.

After system training it is ready to be used to diagnose new bridge deterioration case. Two test examples are use for system verification, one for crack diagnosis and one for spalling diagnosis. The input data of the bridge including survey and inspection information which shows that a crack occurs in superstructure with a specific condition mark, and a spalling in support-structure with another given condition mark. The inference results, along with expert opinions indicate that the particular crack was caused by 'loads and its likes' with a confidence degree of 'very true', and that the spalling was caused by 'others' with a confidence degree of very true. Both of the results are in accordance with the expert opinion, which suggests 'overloaded' and 'aging' are the causes of the crack and spalling, respectively (Zhao & Chen, 2001, 2002).

5.2 An adaptive neuro-fuzzy inference system for bridge risk assessment

Bridge risks are often evaluated periodically so that the bridges with high risks can be maintained timely. Modeling bridge risks is a challenging job facing Highways Agencies because good mathematical models can save them a significant amount of cost and time.

In this case study an adaptive neuro-fuzzy system (ANFIS) using 506 bridge maintenance projects for bridge risk assessment is introduced. The system can help British Highways Agency to determine the maintenance priority ranking of bridge structures more systematically, more efficiently and more economically in comparison with the existing bridge risk assessment methodologies which require a large number of subjective judgments from bridge experts to build the complicated nonlinear relationships between bridge risk score and risk ratings.

The 506 bridge maintenance projects dataset is randomly split into two sample sets: training dataset with 390 projects and testing dataset with 116 projects. Both the training and testing datasets cover all levels and types of bridge risks.

Inputs to the ANFIS are safety risk rating (SRR), functionality risk rating (FRR), sustainability risk rating (SURR), and environment risk rating (ERR). All inputs range from 0 to 3 with 0 representing *no risk*, 1 *low risk*, 2 *medium risk* and 3 *high risk*. Output to the ANFIS is the risk scores (RSs) of the 506 bridge projects, which ranges from 5 to 99.

With the 390 training dataset, two generalized bell-shaped membership functions are chosen for each of the four inputs to build the ANFIS, which leads to 16 if–then rules containing 104 parameters to be learned. Fig. 7 shows the model structure of the ANFIS that is to be built for bridge risk assessment in this study.
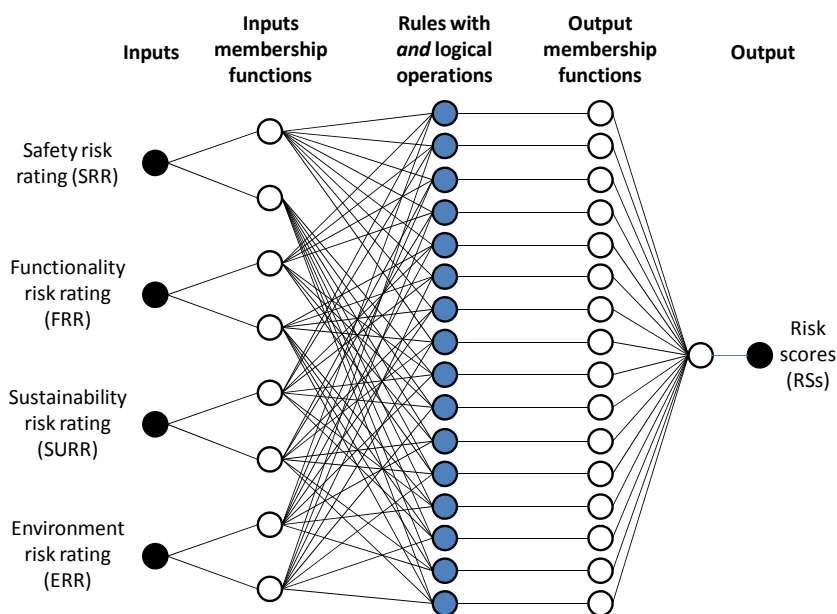

Fig. 7. Model structure of the ANFIS for bridge risk assessment

The developed ANFIS system for bridge risk assessment learns the if–then rules between bridge risk scores and risk ratings from the past bridge maintenance projects and memorizes them for generalization and prediction. It has been observed that ANFIS outperforms artificial neural networks to perform better than multiple regression models (Wang & Elhag, 2007). Differing from artificial neural network, ANFIS is transparent rather than a black box. Its if–then rules are easy to understand and interpret. In this case study the performances of the ANFIS and ANN in modeling bridge risks are compared, where the two models are trained using the same training dataset and validated by the same testing dataset. Comparison shows that the ANFIS has smaller root mean squared error and mean absolute percentage error as well as bigger correlation coefficient for both the training and testing datasets than the ANN model. In other words, the ANFIS achieves better performances than

the ANN model. Therefore, ANFIS is a good choice for modeling bridge risks. Moreover, ANN is a black box in nature and its relationships between inputs and outputs are not easy to be interpreted, while ANFIS is transparent and its if–then rules are very easy to understand and interpret. But the drawback of ANFIS is its limitation to the number of outputs. It can only model a single output. In summary, ANFIS is a good choice and powerful tool for modeling bridge risks (Wang & Elhag, 2008).

5.3 Fuzzy concrete bridge deck condition rating method for practical bridge management system

Bridge management system (BMS) is a tool for structured decision making and planning/scheduling for bridge infrastructure inspection, maintenance and repair or retrofit. Any BMS is basically constructed based on data stored in inventory and inspection databases. One of the important and crucial efforts in managing bridges is to have some criteria to show the current condition of the elements of bridges based on the results from inspection data. As the results are not precise and are related to the depth and extent of the inspectors' expertise, there are some uncertainties in any evaluation. On the other side condition of bridges are rated linguistically in many cases with some kinds of vagueness in description of the bridge element conditions. Based on these facts in this case study a new fuzzy method is introduced to deal with these shortcomings from the uncertain and vague data. The fuzzy bridge deck condition rating method is practically based on both subjective and objective results of existing inspection methods and tools. The parameters of the model are selected as fuzzy inputs with membership functions found from some statistical data and then the fuzziness of the condition rating is calculated by the fuzzy arithmetic rules inherent in the fuzzy expert system. Since one of the most proven and experienced advantages of fuzzy inference systems is the tolerability for noisy (uncertain and vague) data it is believed that this proposed system can be an alternative method for current rating indices amongst many others which are almost used deterministically.

In this case study Fuzzy Inference System is used to translate the concrete bridge deck inspection results to condition rating (Tarighat & Miyamoto, 2009).

In literature the proposed rating methods are resulted from either visual inspection or nondestructive tests. Here, in order to enhance the capabilities of both methods (visual inspection and nondestructive tests) a hybrid inspection results is used to calculate the condition rating of the concrete bridge deck. Fig. 8 shows the type of inspection results.

The linguistic attributes of observed symptoms are defined as following fuzzy sets.

A1 = {No; Yes}
A2 = {NoCracks; HairlineCracks; WideCracks}
A3 = {No; Maybe; Yes}
A4 = {Firm; Moderately; Hollow; Very Hollow}
A5 = {Low; Moderate; High}

Considering Gaussian membership functions for inputs and applying Mamdani's method as fuzzy inference system Fig. 9 shows the proposed system for predicting of bridge deck condition rating. For design of fuzzy inference system 162 rules are defined based on the experts' experience and available facts from previous inspection results. Finally Fig. 10 can be used to convert the crisp condition rating result to linguistic term.
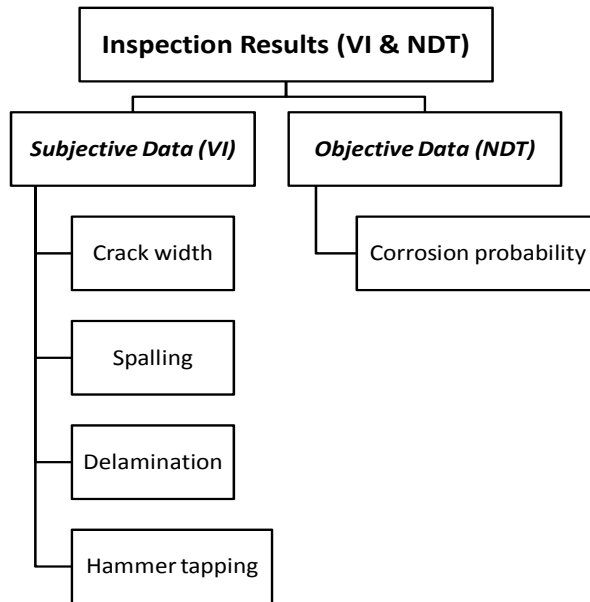
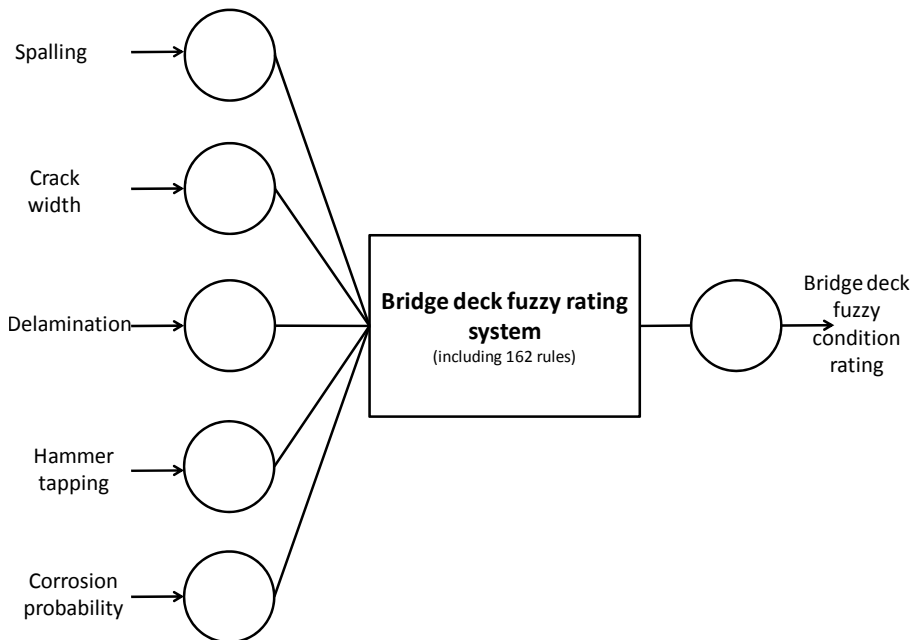Fig. 8. Type of inspection results

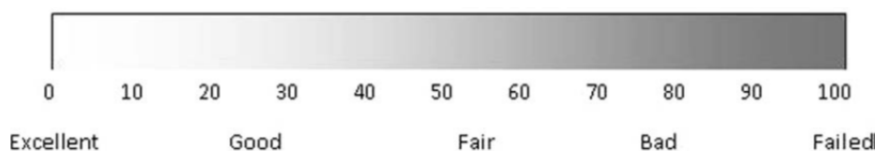Fig. 9. Proposed fuzzy system for bridge deck condition rating.

Fig. 10. Concrete bridge deck condition rating in linguistic terms.

To verify the proposed method an inspected concrete bridge deck is used. The layout of inspection is shown in Fig. 11. The proposed method is applied to the red slab and green haunch girder of the deck shown in Fig. 11.
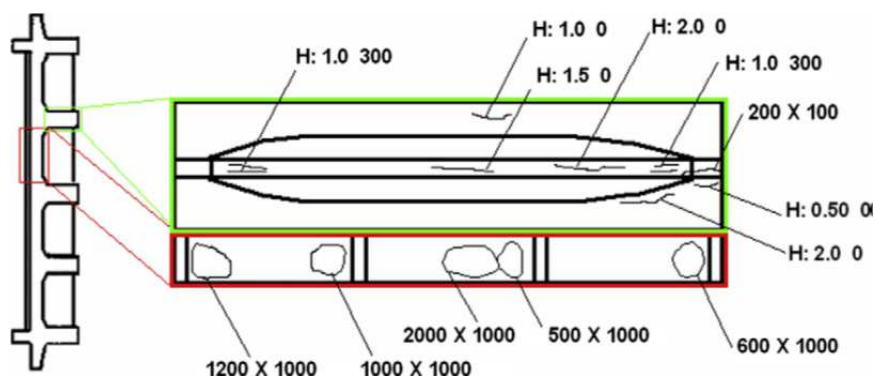

Fig. 11. Concrete bridge deck inspection layout.

Fuzzy condition rating method facilitates data collection in inspection process. No area calculation is required and it needs only the good judgment of the inspector to find out the condition rating. The inspection data is shown in Table 2. Since the symptoms and deterioration/damages of girders and slabs of a deck are totally similar the proposed model can be used for them during bridge inspection process.

Deck element	Spalling condition	Crack width condition	Delamination condition	Hammer tapping condition	Corrosion probability condition	Fuzzy condition rating
Slab (Red Area)	20	50	90	50	10	75.2
Girder (Green Area)	80	70	40	70	90	78.9

Table 2. Inspection data for typical slab and haunch girder of the reinforced concrete bridge deck.

To compare these results with a well-defined and in-use condition rating method the following seven-state rating scale, which reflects the different damage states associated with chloride-induced corrosion is used (Federal Highway Administration (FHWA), 1995; Morcous, Lounis, & Mirza, 2003). Table 3 provides a summary description of the adopted condition rating system as the benchmark.

Description	Condition rating (CR)
Excellent condition: no contamination; no corrosion; no repaired area	1
Very good condition: minor cracks, no spalls or delaminations; chloride contaminated or repaired areas 62% (of total deck area)	2
Satisfactory condition: spalls or delaminations 62%; cracked, corroded, contaminated, or repaired area 610%	3
Fair condition: spalls or delaminations 65%; cracked, corroded, contaminated, or repaired area 620%	4
Poor condition: spalls or delaminations 610%; cracked, corroded, contaminated, or repaired area 625%	5
Critical condition: spalls or delaminations 615%; cracked, corroded, contaminated, or repaired area P25%	6
Failed condition (total loss of serviceability or functionality): extensive spalling, delamination, repaired areas P30%; maintenance required	7

Table 3. Condition rating system for concrete bridge decks (Federal Highway Administration (FHWA), 1995; Morcous et al., 2003).

Based on Table 3 the condition rating for typical slab and haunch girder under consideration are 6 and 5. Scaling is required to be able to compare the results, therefore the above mentioned numbers should be multiplied by 14.28 to get a 100-based score system. Table 4 provides the comparison. It is shown that results from proposed method can estimate the condition rating very well.

Deck Component	Proposed fuzzy condition rating system		Scaled (to 100) Condition Rating based on the selected references		Absolute value Difference of the proposed method to the selected references
	Numerical value	Linguistically index	Numerical value	Linguistically index	
Slab CR	75.2	Bad	85.7	Critical condition	10.5
Girder CR	78.9	Bad	71.4	Poor condition	7.5

Table 4. Comparison of the condition ratings from two methods.

5.4 A two stage method for structural damage identification using an adaptive neuro-fuzzy inference system and practice swarm optimization

All the above three case studies are of diagnosis and assessment types. As declared earlier another important task of any BMS or BHMS is the possibility to locate damaged area or components. The present case study is about damage detection (Fallahian & Seyedpoor, 2010).

In this case study, an efficient methodology is proposed to accurately detect the sites and extents of multiple structural damages. The proposed methodology has two main phases

combining the adaptive neuro-fuzzy inference system (ANFIS) and a particle swarm optimization (PSO) as an optimization solver. In the first phase, the ANFIS is employed to quickly determine the structural elements having the higher probability of damage from the original elements. In the second phase, the reduced damage problem is solved via the particle swarm optimization (PSO) algorithm to truthfully determine the extents of actual damaged elements.

Structural damage detection techniques can be generally classified into two main categories. They include the dynamic and static identification methods requiring the dynamic and static test data, respectively. Furthermore, the dynamic identification methods have shown their advantages in comparison with the static ones. Among the dynamic data, the natural frequencies of a structure can be found as a valuable data. Determining the level of correlation between the measured and predicted natural frequencies can provide a simple tool for identifying the locations and extents of structural damages. Two parameter vectors are used for evaluating correlation coefficients. A vector consists of the ratios of the first n_f vector natural frequency changes ΔF due to structural damage, i.e.

$$\Delta F = \frac{F_h - F_d}{F_h} \tag{8}$$

where F_h and F_d denote the natural frequency vectors of the healthy and damaged structure, respectively. Similarly, the corresponding parameter vector predicted from an analytical model can be defined as:

$$\delta F(X) = \frac{F_h - F(X)}{F_h} \tag{9}$$

where $F(X)$ is a natural frequency vector that can be predicted from an analytic model and $X^T = \{x_1, ..., x_i, ..., x_n\}$ represents a damage variable vector containing the damage extents $(x_i, i=1, ..., n)$ of all n structural elements.

Given a pair of parameter vectors, one can estimate the level of correlation in several ways. An efficient way is to evaluate a correlation-based index called the multiple damage location assurance criterion (MDLAC) expressed in the following form:

$$MDLAC(X) = \frac{\left|\Delta F^T . \delta F(X)\right|^2}{(F^T . \Delta F)[\delta F^T(X) . \delta F(X)]} \tag{10}$$

The MDLAC compares two frequency change vectors, one obtained from the tested structure and the other from an analytical model of the structure. The MDLAC varies from a minimum value 0 to a maximum value 1. It will be maximal when the vector of analytical frequencies is identical to the frequency vector of damaged structure, i.e., $F(X) = F_d$.

The key point of this case study is that ANFIS concept can be effectively utilized to determine the most potentially damaged element (MPDE) of an unhealthy structure. For this, some sample structures having the damaged elements are randomly generated based on the damage vector X as the input and the corresponding $MDLAC(X)$ as the output. In other words some scenarios are defined for damaged structures. Then, an exhaustive search

is performed using the ANFIS within the available input-output data to arrange the structural elements according to their damage potentiality. Essentially, the exhaustive search technique builds an ANFIS network for each damage variable from original ones and trains the network for a little epoch and reports the performance achieved. The step by step summary of the exhaustive search algorithm for determining the MPDE of an unhealthy structure is as follows:

a. Establish the pre-assigned parameters of the intact structure.
b. Randomly generate a number of sample structures having some damaged elements within the allowed space of damage variables X.
c. Determine the natural frequencies of the sample structures using a conventional finite element analysis.
d. Estimate the level of correlation between unhealthy structure and each sample structure by evaluating the $MDLAC(X)$ index via equation (10).
e. Randomly split the sample structures into two sets with some samples for training and remaining samples for testing the ANFIS, respectively.
f. Build an ANFIS model for each damage variable as the input and the $MDLAC(X)$ as the output. This leads to n ANFIS models equal to the total number of structural elements.
g. Calculate the root mean square error (RMSE) for training and testing sets as:

$$RMSE = \sqrt{\frac{1}{n_t}\sum_{i=1}^{n_t}(ac_i - pr_i)^2} \qquad (11)$$

where ac and pr represent the actual and predicted values of the $MDLAC(X)$, also n_t is the number of training or testing samples.

a. Sort the structural elements according to increasing their training $RMSE$ values and select the first m arranged elements, having the least $RMSE$ errors, as the reduced damage vector, denoted here by $X_r{}^T = \{x_{r1}, x_{r2}, …, x_{rm}\}$.
b. End of the algorithm.

Now it is time to identify damage using optimization algorithms. As mentioned above, the MDLAC index will reach to a maximum value 1 when the structural damage occurs. This concept can be utilized to estimate the damage vector using an optimization algorithm. For this aim, the unconstrained optimization problem with discrete damage variables reduced may be stated as:

$$\begin{aligned}
&\text{Find} && X_r^T = \{x_{r1}, x_{r2}, ..., x_{rm}\} \\
&\text{Minimize}: && w(X_r) = -MDLAC(X_r) && (12) \\
&&& x_{ri} \in R^d, \quad i = 1,...,m
\end{aligned}$$

where R^d is a given set of discrete values and the damage extents x_{ri} (i= 1, …,m) can take values only from this set. Also, w is an objective function that should be minimized.

The selection of an efficient algorithm for solving the damage optimization problem is a critical issue. Needing fewer structural analyses for achieving the global optimum without trapping into local optima must be the main characteristic of the algorithm. In this study, a

particle swarm optimization (PSO) algorithm working with discrete design variables is proposed to properly solve the damage problem.

In order to show the capabilities of the proposed methodology for identifying the multiple structural damages, two illustrative test examples are considered. The first example is a cantilever beam discussed in detail and the second one is a bending plate discussed in brief. The numerical results for these examples demonstrate that the combination of the ANFIS and PSO can produce an efficient tool for correctly detecting the locations and sizes of damages induced (Fallahian & Seyedpoor, 2010).

6. Conclusion

Fuzzy logic inference methods can be used for managing bridges. Models based on FIS consider simultaneously several facts or knowledge combinations as rules and indicate the final answer or guess which is very close to practical existing situation as the hypothesis of the greatest belief. The reasoning process is very clear and easy to understand by users who are not experts in the performance of decision support systems. For bridge inspection no deteriorated area calculation is needed and the only requirement is the good inspector's judgment. It should be noted that fuzzy systems can tolerate some noise to predict the outputs. This means that during bridge deck inspection if in some cases judgment is not correct, but close to real condition, the proposed method can estimate the condition very well without a major difference from practical point of view. It is clear that in deterministic methods incorrect judgment or decision changes the category of the predefined condition and overall condition rating drastically. Another point that should be notified is that FIS can be applied in areas with high nonlinearity. When nonlinearity is high the prediction accuracy is expected to be improved by using ANFIS comparing to Mamdani's method. Accuracy of the method can be improved when an adaptive optimization method is used for constructing similar model based on the training data from inspections. FIS modeling is suitable for prioritization of repairing bridges and budgeting tasks in which relatively simple and practical reasoning is required for decision makers. Even in cases that human expertise is not available, we can still set up intuitively reasonable initial membership functions and start the learning process to generate a set of fuzzy if-then rules to approximate a desired data set. The efficiency of rule-based reasoning can be improved by comparing different inference methods. Generally the inferred results are in agreement with the expert's opinion, and can provide substantial assistance to authorities in their planning.

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Fuzzy Inference System - Theory and Applications

Edited by Dr. Mohammad Fazle Azeem

This book is an attempt to accumulate the researches on diverse inter disciplinary field of engineering and management using Fuzzy Inference System (FIS). The book is organized in seven sections with twenty two chapters, covering a wide range of applications. Section I, caters theoretical aspects of FIS in chapter one. Section II, dealing with FIS applications to management related problems and consisting three chapters. Section III, accumulates six chapters to commemorate FIS application to mechanical and industrial engineering problems. Section IV, elaborates FIS application to image processing and cognition problems encompassing four chapters. Section V, describes FIS application to various power system engineering problem in three chapters. Section VI highlights the FIS application to system modeling and control problems and constitutes three chapters. Section VII accommodates two chapters and presents FIS application to civil engineering problem.

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