Deliverable D9
Review use of Neural Networks, classify defects and guidelines for condition assessment

Status (P)

BRIME
PL97-2220

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Norwegian Public Roads Administration (NPRA)

Slovenian National Building and Civil Engineering Institute (ZAG)

Date: October 2001

PROJECT FUNDED BY THE EUROPEAN
COMMISSION UNDER THE TRANSPORT
RTD. PROGRAM OF THE
4th FRAMEWORK PROGRAM

Review use of Neural Networks, classify defects and guidelines for condition assessment

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EXECUTIVE SUMMARY

SCOPE

Europe has a large capital investment in the road network including bridges, which are the most vulnerable element. As bridges age, deterioration caused by heavy traffic and an aggressive environment becomes increasingly significant resulting in a higher frequency of repairs and possibly a reduced load carrying capacity.

The purpose of this project is to develop a framework for the management of bridges on the European road network that enables bridges to be maintained at minimum overall cost taking all factors into account. These include condition of the structure, load carrying capacity, rate of deterioration, effect on traffic, life of the repair and the residual life of the structure.

SUMMARY

This report gives an overview of use of Neural Networks, fuzzy logic and genetic algorithms in structural and civil engineering with emphasis on their use in bridge management. An important part of bridge management is inspection and condition assessment of structures. To carry out a proper condition assessment, a comprehensive catalogue of defects is needed as well as methods to quantify defects with respect to their intensity, extent, and possible impact on the users safety and durability of the structural elements. It is the second of two reports delivered by Workpackage 1 -"Condition Assessment". The main objective of this workpackage is to derive general guidelines for condition assessment of structures.

The first and the second chapter of the report discuss the use methods of artificial intelligence in civil and structural engineering, and, in particular, in a Bridge Management System (BMS). It is emphasised that neural networks and other methods of artificial intelligence seem to offer a promising way of handling the complex information that lies behind the deterioration of a structure and treating such problems in an efficient and cost-effective manner.

Chapter 3 provides an overview of use artificial intelligence (AI) in civil and infrastructure engineering. Three methods of AI are briefly described: neural networks, genetic algorithms and fuzzy sets.

Chapter 4 describes the use of neural networks in bridge management. The use of CAE (Conditional Average Estimator) neural networks for categorisation of damaged locations on reinforced and prestressed concrete structures is described in detail. An important part of this chapter is a description of fuzzy logic and a comparison of CAE – three layer BP NN (Back Propagation Neural Networks) – ID3 (fuzzy logic) for a simple case study of damage categorisation.

Chapter 5 gives a review of causes of defects and deterioration in bridge structures as well as a classification of defects in relation to their main characteristics. Chapter 6 gives short guidelines for condition assessment..

IMPLEMENTATION

An overview of the of AI procedures, given in this Deliverable, provides a basis for discussion and further work on how to implement these methods for condition assessment evaluation for defects and deterioration processes. They can be useful for categorisation of defects on structures with a large number of damaged locations.

REVIEW USE OF NEURAL NETWORKS, CLASSIFY DEFECTS AND GUIDELINES FOR CONDITION ASSESSMENT

ABSTRACT

Engineeering judgement can play an important role in the assessment of the condition of structures. This is especially true when inspectors don't have a lot of experience, and guidelines for inspection and condition assessment of structures are not well defined. To overcome such obstacles, new mathematical tools, such as neural networks and genetic algorithms, as well as classical probabilistic modelling and risk analysis methods are being introduced. The methods themselves are only as good as the input values for modelling and other random variables. An important part of the assessment is continuous improvement of both the catalogues of defects and methods for evaluation of their condition. Therefore, different types of periodic inspection supplemented by non-destructive testing techniques are very important for improving knowledge on defects and to reduce uncertainties based on engineering judgement to an acceptable level.

1.0 INTRODUCTION

A reliable treatment of natural phenomena is based on measurements and descriptions based on relationships between the observed results. From the theoretical point of view, the relationships are most appropriately specified in terms of abstract mathematical models representing mathematical laws. But from the practical point of view, simulated analogue models based on electronic devices are sometimes more convenient. A neural networks and/or neural network-like system is one such analogue model.

In recent years there has been an increasing number of studies and applications of intelligent systems in civil engineering. They are used to handle the data obtained from observation and/or measurements in the field and/or in the laboratory. The literature review showed that four methods are mainly used in structural engineering. These are expert systems, neural networks, fuzzy logic and genetic algorithms. The applications include: design optimisation of reinforced concrete members and frames, analysis of bridge condition rating data, optimisation of bridge deck rehabilitation and pavement rehabilitation. A short review of some applications of Artificial Intelligence in civil and structural engineering is presented also in Deliverable D3.

Assessment of deteriorated structures is a very important part of bridge management and must therefore be carried out by experienced engineers. Assessment is a combination of a pre-defined assessment method as well as engineering judgement. Some subjectivity or engineering judgement is always part of an assessment of structural condition. To reduce the degree of subjectivity continuing education is needed as well as a periodic improvement of the catalogue of defects and methods for quantification of defects. In the future, artificial intelligence methods will be increasingly used for the assessment of deteriorated structures. Special care is needed in developing procedures for assessment of deterioration of repairs and new materials, such as composite materials and aluminium that are used in the construction of new structures.

2.0 OBJECTIVES FOR USE ARTIFICIAL INTELLIGENCE (AI)

The field of bridge management itself is large and very complex. Different parts of it can be effectively handled and solved by classical mathematical tools. But some parts, due to the very complex nature of many processes that run behind (i.e. degradation of concrete structure during the exploitation), are based on so called engineering judgement. In information era, when the help of computers is inevitable, such type of knowledge (information!) is not as suitable as information captured in abstract mathematical models. So far, intelligent systems, during the last decade some of them known as expert systems and neural networks, seem to be a promising way of how to handle complex information captured in expert's knowledge and measured data that describe different phenomena.

To make applicable models and/or to get applicable results (which is the main purpose of the project) from a huge amount of knowledge that many experts from different countries can contribute to, is a very difficult task. The main idea of using neural networks is to show how modern techniques are able to deal effectively with huge amount of measured data and engineering judgement in bridge management. Note that we have dealt with only simple examples which are presented in this report – but they show powerful possible future applications in bridge management.

3.0 REVIEW OF USE AI IN CIVIL AND INFRASTRUCTURE ENGINEERING

Artificial intelligence, a branch of computer science (or soft science, from some sources), consists of several computing paradigms, including knowledge-based systems known from the past also as expert systems, neural networks (learning and adaptation), fuzzy set theory (knowledge representation via fuzzy IF – THEN rules), and genetic algorithms and/or simulated annealing. For the sake of completeness?, the most important paradigms, mentioned above, are briefly presented. The focus in this report is mainly on neural networks and their applications to BMS.

3.1 Methods

3.1.1 Artificial neural networks (/A/NNs)

An ANN takes after its biological analog through its composition of nodes and the connections among them. The advantages of using ANNs include improvements in the speed of operation by parallel implementation either in hardware or in software.

ANNs are a kind of algorithms with certain characteristics that can be used to describe different (natural) phenomena or to solve some certain optimisation tasks. Different types of NNs are used for different problems. As an intelligent systems the back-propagation (BP) NN is often used. The common approach to the construction of optimisation neural networks is to formulate the problem in terms of minimising a cost or energy function - this approach is known as the Hopfield network (Hopfield and Tank, 1985). Self-organising of neurons (Grabec and Sachse, 1997) is also an optimisation problem which can be connected to the cost minimisation.

Some attempts have been made in the past to show how the ANNs can be used in Bridge Management Systems (BMS). It can be concluded, that the time dimension can be modelled by dynamic programming, whereas the road network dimension can be easily simulated by a neural network. ANNs have the potential to be used to allocate funds for large number of bridges with unlimited viable alternatives.

3.1.2 Genetic algorithms

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomised information exchange to form a search algorithm with some innovative flair of human search. Genetic algorithms as an optimisation method have achieved increasing popularity as researchers have recognised the shortcomings of calculus-based and enumerative schemes.

Genetic algorithms are different from standard optimisation and search procedures in four ways:

- GAs work with a coding of the parameter set, not the parameters themselves,
- GAs search from a population of points, not a single point,
- GAs use payoff (objective function) information, not derivates or other auxiliary knowledge,
- GAs use probabilistic transition rules, not deterministic rules.

3.1.3 Fuzzy sets

Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth – truth values between “completely true” and “completely false”. It was introduced by Dr.Lotfi Zadeh in the 1960’s as a means to model the model uncertainty of natural language. Just as there is a strong relationship between Boolean logic and the concept of a subset, there is a strong relationship between fuzzy logic and fuzzy subset theory. Since the introduction of the fuzzy logic, fuzzy calculus, fuzzy differential equations and so on have been introduced in different field of application of artificial intelligence.

3.2 Civil and Structural Engineering

A great number of articles on neural networks and their applications in civil and structural engineering show the importance of this branch. It is impossible to review all what was published in the past. Therefore, we have limited ourselves to the recent research only. In addition, in references the list of most important (fundamental) books and international journals, which are connected to civil and structural enginnering, is given.

Neural networks in civil and structural engineering can be used in different areas, i.e. in engineering structural assessment, in structural analysis and design, to finite element problems, in control, in construction engineering, etc. Typical neural network applications in civil engineering are use of NN in hydro-meteorological modelling (Jayawardena and Fernando, 1995), evaluation of seismic liquefaction (Goh, 1995) and NN multiobjective and multiresource decision support system (Wei and Singh, 1995).

Neural networks can be used for aproximations in structural analysis (Jenkins, 1995). Zeng (Zeng, 1995) developed neurons element for structural analysis, networks for structural analysis, mathematical principle and implementation procedure. Kirkegaard (Kirkegaard, 1995) investigated two different partially recurrent neural networks strcutured as Multi Layer Perceptrons (MLP) for time domain identification of a non-linear structure. Watson et al (Watson et al, 1995) examined the possibility of using a feed-forward, multilayer NN to identify and locate changes in the pile’s cross section. Similary, Takanashi and Yoshioka (Takanashi and Yoshioka, 1995) used a multilayer perceptron network trained with the backpropagation algorithm for detecting location and size of the fault in structural element.

Yeh (Yeh, 1998) presented an augmented NN, a novel neural network architecture, and examined its efficiency and accuracy. His experimental results demonstrated that the presented network’s logarithm and exponent neurons provide a markedly enhanced network architecture capable of improving the network’s performance for structural engineering applications. Thirumalaiah and Deo (K. Thirumalaiah and Deo, 1998) used a technique of NN fro real-time forecasting of stream flows during storms. Shi and AbouRizk (J.Shi & S.S.AbouRizk, 1998) described resource-based modeling as a general methodology for automating the modeling process of construction simulation.

3.3. Infrastructure

A review of different applications of AI in bridge engineering and infrastructure has already been presented by Reich in 1996 (Reich, 1996). His review and proposed model comprises studies and applications from conceptual design, aesthetics, analysis, applied loads, design subtasks, planning, erection, monitoring, function and monitoring structure, maintenance, inspection and evaluation, retrofit and sheduling.

Cattan and Mohammadi (Cattan and Mohammadi, 1997) presented the application of NN systems in developing the relation between subjective ratings and and bridge parameters as well as that between subjective and analytical ratings. It was shown that NNs can be trained and used successfully in estimating a rating based on bridge parameters.

Mikami et al (Mikami et al, 1998) presented a study, where a system to reason the residual axial forces of high strength bolts of steel bridges was built based on a NN with the faculty of pattern recognition. It was shown that the system could reason with a considerable accuracy. Chikata et al (Chikata et al, 1998) presented inverse analysis by NN of scenery evaluation of planted concrete structures (concrete retaining walls). The efficacy of presented NN inverse analysis and genetic algorithm analysis using fuzzy-set theory was compared.

Lakmazaheri (Lakmazaheri, 1996) presented a framework for developing intelligent CAD systems that support deductive reasoning. His application involves representing the geometry of standard bridges using the language of predicate logic, and generating, modifying and verifying the geometry of standard bridges via logical inference.

4.0 NEURAL NETWORKS (NN) IN BMS

4.1 CAE

4.1.1 Introduction

The problem addressed in this report is how to estimate the unknown parameters as a function of known data. The first and second set of variables will be called the output and input variables, respectively. In order to determine unknown output variables from known input variables, a database containing sufficient well-distributed and reliable empirical data is needed. The data base should include both measured values of output variables and the corresponding input variables. One particular observation which is included in the database, can be described by a sample vector. The input and output variables correspond to the components of this vector. The database consists of a finite set of sample vectors. It should be noted that often the major difficulty lies in obtaining a appropriate data base.

4.1.2 Definition

According to the CAE method, each of the output variables corresponding to the vector under consideration (i.e. a vector with known input variables and output variables to be predicted) can be estimated by the formulae (Grabec and Sachse, 1997, Perus et al, 1994):

$$r_k = \sum_{n=1}^{N} C_n \cdot r_{nk}$$

where

$$C_n = \frac{c_n}{\sum_{j=1}^{N} c_j}$$

and

$$c_n = \exp\left[\frac{-\sum_{i=1}^{L}(p_i - p_{ni})^2}{2w^2}\right]$$

Here r_k is the k-th output variable, r_{nk} is the same output variable corresponding to the n-th vector in the data base, N is the number of vectors in the data base, p_{ni} is the i-th input variable of the n-th vector in the data base, p_i is the i-th input variable corresponding to the vector under consideration, and L is the number of input variables.

Equations suggest that the estimate of an output variable is computed as a combination of all output variables in the data base. Their weights depend on the similarity between the input variables p_i of the vector under consideration, and the corresponding input variables p_{ni} pertinent to the sample vectors stored in the data base. C_n is a measure of similarity. Consequently, the unknown output variable is determined in such a way that the computed vector composed of given and estimated data is most consistent with the sample vectors in the data base.

The parameter w is the width of Gaussian function which will be called the smoothness parameter. It determines how fast the influence of data in the sample space decreases with increasing distance from the point whose co-ordinates are determined by the components (input variables) of the vector under consideration. The larger the value of w is, the more slowly this influence decreases. Large w values exhibit an averaging effect. In principle, a proper value of w should correspond to a typical distance between data points. In this case the

CAE method yields a smooth interpolation of functional relation between the input and output variables.

In some applications, a non-constant value of w yields more reasonable results than a constant value. When using non-constant w values, all equations can still be used, but proper, locally estimated values of w_i should be taken into account. The formula for c_n can be rewritten as

$$c_n = \exp\left[-\sum_{i=1}^{L} \frac{(p_i - p_{ni})^2}{2w_i^2} \right]$$

where different values of w_i correspond to different input variables.

It should be noted that presented equations were mathematically derived, based on the assumption of a constant uncertainty of the input data. The extension of the applicability of these equations to non-constant w values (see equation above) is, however, based on physical considerations. Whereas a constant w corresponds to a sphere in an L-dimensional space (L is the number of input variables), corresponds a non-constant w value to a multi-axial ellipsoid in the same space.

The choice of an appropriate value of w depends, as well as on the distribution of data, on the latter's accuracy and on the sensitivity of the output variables to changes in the input variables. Some engineering judgement based on knowledge of the investigated phenomenon, and a trial and error procedure, are needed to determine appropriate value(s) for w.

In the case of prediction of the seismic capacity of structural walls which was the first application of the CAE in structural engineering (Perus et al, 1994), all the variables were normalized, and a constant value of w was used. In the case of prediction of ground motion characteristics (Fajfar & Peruš, 1997), a constant w value does not yield satisfactory results. Based on the physical considerations, and after the application of a trial and error procedure, it was decided in this case to use different w values for the different input variables.

In order to check the possible dispersion of the unknown output variable r_k around the prediction, a measure E_k, which will be called local standard deviation, was introduced. E_k is defined by the equation

$$E_k = \sqrt{\frac{1}{N_{mw}} \sum_{n=1}^{N_{mw}} (r_{nk} - r_k)^2}$$

where N_{mw} is the number of data inside a subspace within the data base. In the case of two input variables, this subspace is defined as a rectangle, with its centre at a point determined by the co-ordinates X_1 and X_2 (input variables of the vector under consideration), and with half-sides $m\, w_{X1}$ and $m\, w_{X2}$, where m is an arbitrarily chosen constant and w_{X1} and w_{X2} are the smoothness parameters corresponding to X_1 and X_2, respectively. In the case of more than two input variables, the subspace is defined analogously. The dimension of the subspace is equal to the number of input variables (L). It should be noted that E_k is a function of all of the input variables. Large values of m (e.g. 10 or more) produce an averaging effect, and yield a more or less constant value of E_k. Small values of m (e.g. 1 or less) lead to large fluctuations in E_k. Reasonably smooth E_k values, which correspond favourably to the standard deviations observed in previous attenuation studies, can be obtained using $m = 2$.

4.2 Fuzzy logic / ID3

4.2.1. Introduction

Algorithm Inductive Decision Tree (I.D.3) is proposed by QUILAN in 1979. The I.D.3 is a training system of a supervised (with professors) manner in which the individuals can be divided in several classes according to certain numbers of characteristics. I.D.3 method's output shapes acquaintance in an arboraceous form, so that the IF – THEN rules can be constructed. This tree-like form is founded on the theory of transmission – information. When the causality rule can't be established, a wrong data is certainly introduced in the database. If the neuron network system is so called a black box then I.D.3 is a transparent box. It is easy to introduce the fuzzy logic and the theory of possibility into this I.D.3 method which can be adapted for different customs of bridge's maintenance (conviviality) of each country. It is also easy to class the bridges in field immediately by using minimum attributes.

4.2.2 Definition

1) $I = \{i_1, \ldots, i_i\}$ set of individuals.
2) $C = \{c_1, \ldots, c_c\}$ set of class instituted "decision" or "diagnosis".
3) $A = \{a_1, \ldots, a_a\}$ set of attributes (essential characteristic or inherent property).
4) $V_q = \{v_{q1}, \ldots, v_{qv}\}$ set of the values associated with attribute $a_q \,(q \in [1, a])$.
5) Definition of the SHANNON's entropy.

The entropy is the quantity of information brought by the recognition of the class of one individual between two classes c_1 and c_2 with the respective probability P_1 and P_2.

$$E = P_1 \log_2(\frac{1}{P_1}) + P_2 \log_2(\frac{1}{P_2})$$

6) Definitions of $n_{\bullet}^{j}$, $n_{k}^{\bullet}$ and $n_{\bullet}^{\bullet}$

For each of the attribute a_q, ($q \in [1, a]$), we can establish one table of contingent :

Attributes	C \ V_q	c_1	• • •	c_j	• • •	c_c	$n^{\bullet}$
a_q	v_{q1}	n_1^1		n_1^j		n_1^c	$n_1^{\bullet}$
	⋮						
	v_{qk}	n_k^1		n_k^j		n_k^c	$n_k^{\bullet}$
	⋮						
	v_{qv}	n_v^1		n_v^j		n_v^c	$n_v^{\bullet}$
	$n_{\bullet}$	$n_{\bullet}^1$		$n_{\bullet}^j$		$n_{\bullet}^c$	$n_{\bullet}^{\bullet}$

n_k^j : The number of individual verifying the modality of decision j, ($j \in [1, c]$), and the modality k of the value of the attribute a_q, ($q \in [1, a]$, $k \in [1, v]$).

$$n_{\bullet}^j = \sum_{k=1}^{v} n_k^j \qquad \text{for } j \in [1, c]$$

$$n_k^{\bullet} = \sum_{j=1}^{c} n_k^j \qquad \text{for } k \in [1, v]$$

$$n_{\bullet}^{\bullet} = \sum_{j=1}^{c} n_{\bullet}^j = \sum_{k=1}^{v} n_k^{\bullet}$$

7) Definition of the entropy of decision $ED(c, a_q)$

The ED is defined as following :

$$ED(c, a_q) = \sum_{j=1}^{c} \left(n_{\bullet}^j / n_{\bullet}^{\bullet} \right) \log_2 \left(n_{\bullet}^{\bullet} / n_{\bullet}^j \right)$$

$ED(c, a_q)$ measures the indetermination of the individuals of the running knot in the good class

6) Definition of conditional entropy $EC\,(c / v_{qk})$

The conditional entropy c relative to the modality v_{qk} of the attribute a_q is defined :

$$EC\,(c / v_{qk}) = \sum_{j=1}^{c} \left(n_k^j / n_k^{\bullet} \right) \log_2 \left(n_k^{\bullet} / n_k^j \right)$$

It measures the information that brought by the acquaintance of the v_{qk} in the determination of the class of individual of the running knot.

7) Definition of the conditional mean entropy $ECM\left({c}/{a_q} \right)$

$$ECM\left({c}/{a_q} \right) = \sum_{k=1}^{v} \left({n_{k\bullet}}/{n_{\bullet\bullet}} \right) \times EC\left({c}/{v_{qk}} \right)$$

It measures the indetermination of classification, when we know the information that brought by v_{qk} distribution in difference classes.

8) Definition of information's gain $GI(c, a_q)$

$$GI(c, a_q) = ED\left({c}/{a_q} \right) - ECM\left({c}/{a_q} \right)$$

4.2.3 Algorithm I.D.3

1.1 BEGIN

1) $N \subseteq E$ (N : running_knot; E : set of individuals)
2) N **:** = E (all individuals belong to the running_knot)
3) **IF** N is a terminal_knot (all individuals of N belong to the same class)
   THEN associate the class to individuals in the terminal_knot N.
   END for the terminal_knot.

   IF NOT
   For each a_q
   Calculate $ED(c, a_q)$
   Calculate $EC\left({c}/{v_{qk}} \right)$
   Calculate $ECM\left({c}/{a_q} \right)$
   Calculate $GI(c, a_q)$ (the maximum GI of a_q is chosen)
4) Partition running_knot into N_k knots, $k \in [1, v]$. (v is the number of 'value' in the attribute a_q and N_k are the children of the running_knot N)
5) For each N_k : go to 3)

1.2 END

Remarks:

1. The preceding algorithm shows that a tree can be constructed from knot_parent to knot_children. It means that the " IF THEN rules " can be easily established and a black box becomes a transparent box.

2. The improvement of I.D.3 is called neuro-fuzzy I.D.3. In this new method the membership functions of fuzzy logic and residual appurtenances are introduced for the fuzzy databases.

4.3 Damage categorisation by CAE NN

4.3.1 General

During the inspection of deteriorated structures a lot of information is obtained. They are based on visual observation and on measurements on site or in the laboratory. Great deal of so collected information is related to deterioration of the concrete structures due to corrosion of the reinforcement. These measurements (half-cell potentials, depth of concrete cover, air permeability, resistivity, chloride concentrations profiles, pH at the reinforcement level, carbonation depth) are used to determine the state of the reinforcement corrosion. The results of each method used in measurements are interpreted in terms of likelihood of corrosion (unlikely, probable, almost certain) or in probability of corrosion process. To determine the state of corrosion (possibility of initiation, progress) of the reinforcement, especially in the cases where there are not yet visible traces of corrosion, the result of single type of test or measurement is usually not sufficient. Therefore some combination of several tests will usually be required.

In the past some methods has been developed for categorisation of deteriorated bridge deck. One of them is the method, described in the literature (Pennsylvania, 1987). It is based on visible spalls and delaminations and measured electrochemical potentials. Based on the prescribed criteria, deterioration category classification can be made. The other approach is to classify damages and recommended repair procedures with respect to type of structure (M.K.Söderquvist, 1998).

The idea of using NN in one segment of the bridge management came from the need of categorisation of deterioration spots on large bridge structures with a lot of deteriorated locations. The basis for using NN is to obtain data of damaged spots from the detailed inspection.

The first step is mapping all the relevant damages on the structure. At the same time a visual categorisation of all detected deteriorated spots is performed. Categorisation is made of five categories. Categories are based on visual assessment of: intensity of wetting, depth of delaminated spots, spalling of the concrete cover, width of the cracks, width of opened joints of pre-cast elements, corrosion of the reinforcement and/or tendons, surface imperfection. For all deterioration categories some general repair procedures are given. If the structure has a lot of damaged spots, on a few representative deteriorated spots of all detected categories a field measurements and some laboratory test are performed like electrochemical potentials, carbonation depth, pH at the reinforcement level, concrete permeability, chloride profile, concrete cover. In the future also some additional data of other type of test can be added. Based on the results of measurements a new categorisation is made. With comparison of categorisation based on measurements with visual categorisation on the same spots the agreement between two of them can be assessed.

Because categorisation should not be too subjective, but based on the results carried out on selected deteriorated spots, a general mathematical model covering the whole hyperspace of all possible combinations of the selected parameters has been developed. The model that has been chosen to handle all obtained date is known as the neural network-like approach - CAE.

It should be noted that two different models were developed for damage categorisation – first one based on visually estimated parameters (visual model), and the second one, based on test data (experimental model).

4.3.2. Developing damage categorisation model by CAE

As mentioned above, objective of WP1 is to develop a procedure for quantifying the condition of a bridge. Therefore, a neural network approach is utilised for automatic (computerised) categorisation of deteriorated parts of the bridge. (Note, that similar, but more simple model was already developed at ZAG).

To make such an approach as efficient as possible, we need a good and efficient database. Therefore, a questionnaire filled out by experts, serves as a database for neural network model for damage categorisation (and optimal repair strategy of the deteriorated parts of the bridge structure).

4.3.2.1. Input variables of visual model

Visual signs of concrete deterioration due to reinforcement corrosion caused by chloride ingress and/or carbonation have many stages, which primarily depends on the quality of the concrete and thickness of the concrete cover. Parameters of concrete surface, which are used in categorisation based on visual assessment, are shortly described in table 2. The assessment of each parameter is divided into four categories. The assessment of the crack width on the concrete surface and in the joints between the precast segments is primarily based on the influence the crack has on easier access contaminants to the reinforcement and further corrosion process. The categorisation of surface wetting is based on the experience gained during in-depth inspections of viaducts. The assessment of the corrosion of the reinforcement during visual categorisation is made only if the reinforcement is exposed due to spalls or removal of delaminated concrete, otherwise it is made after testing on-site is finished and inspection windows are made to inspect the condition of the reinforcement.

TABLE 1: VISUAL CATEGORISATION

Visual assessment	Category	Description
Surface condition	**I**	Shallow voids
	II	Deep voids
	III	Honeycomb in the concrete cover
	IV	Honeycomb beyond the level of reinforcement
Scalling, Delamination, Spalling	**I**	Superficial scalling; spalling of concrete surface a few mm thick
	II	Scalling and spalling of concrete cover to the level of stirrups
	III	Scalling, delamination and spalling to the level of the main reinforcement
	IV	Delamination beyond the level of the reinforcement; delamination to the level of prestressing reinforcement
Corrosion	**I**	Superficial corrosion, no reduction in the cross section
	II	Reduction of the reinforcement cross section up to 10%
	III	Reduction of the reinforcement cross section more than 10%; corroded protective sheath and minor to moderate corrosion of prestressing reinforcement;
	IV	Broken reinforcement; heavily corroded or broken prestressing reinforcement;
Cracking, joints	**I**	Crack width $w \leq 0{,}1$ mm
	II	Crack width $0{,}1 < w \leq 0{,}3$ mm
	III	Crack width $0{,}3 < w \leq 1{,}0$ mm
	IV	Crack width $w > 1{,}0$ mm

TABLE 1: VISUAL CATEGORISATION - CONTINUATION

Visual assessment	**Category**	**Description**
Moisture (wetting)	**I**	Very light
	II	Light (only a few signs of rust stains may be visible; thin deposits of efflorescence may be visible)
	III	Heavy (moderate signs of rust stains may be visible; moderate deposits of efflorescence may be visible)
	IV	Very heavy (a lot of signs of rust stains may be visible; thick deposits of efflorescence may be visible)

The CAE experimental model of deterioration category takes into account a number of parameters, which in mathematical sense corresponds to the components of the model vector. One model vector comprises variables representing one distinct deterioration category.

4.3.2.2. Input variables of experimental model

On a few selected location on-site measurements and laboratory tests are carried out. On each selected location concrete cover depth is measured by rebar locator. Depth of carbonation front is measured by fenolftalein test. On-site are also performed gas permeability as well as electrochemical potentials measurements. The interpretation of electrochemical potentials is made upon the standard ASTM C876, although for the convenience of dividing categorisation into four categories the range of electrochemical potential in the range between –200mV and –350 mV is divided into two classes. Concrete cores diameter of 50 mm or more are taken to determine chloride profile and pH value of the concrete at the level of the reinforcement. Parameters, which are used in the test categorisation as well as category classes are presented in table 2.

TABLE 2: TEST CATEGORISATION

Test	Category	Description (boundary values)
Gas permeability (on-site test)	**I**	$g_p \leq 10^{-16}$ m^2
	II	$10^{-16} < g_p \leq 5\times10^{-16}$ m^2
	III	$5\times10^{-16} < g_p \leq 10\times10^{-16}$ m^2
	IV	10×10^{-16} m$^2 < g_p$
Chloride profile (level of critical chloride content = 0,4% b.w.c.) Laboratory test	**I**	0,4% b.w.c. at the middle of concrete cover
	II	0,4% b.w.c. at the level of stirrups
	III	0,4% b.w.c. at the level of main reinforcement
	IV	0,4% b.w.c. beyond the level of the main reinforcement
pH value at the level of the reinforcement Laboratory test	**I**	pH ≥ 11 at the level of the main reinforcement
	II	10 ≤ pH < 11 at the level of the main reinforcement
	III	9 ≤ pH < 10 at the level of the main reinforcement
	IV	pH < 9 at the level of the main reinforcement
Depth of carbonatisation front On-site test	**I**	Less than half of the concrete cover depth
	II	At the level of the stirrups
	III	At the level of the main reinforcement
	IV	Beyond the level of the main reinforcement
Electrochemical potentials On-site test	**I**	Ep > -200 mV
	II	-200 mV ≥ Ep > -275 mV
	III	-275 mV ≥ Ep > -350 mV
	IV	-350 mV > Ep

4.3.2.3 Basic model

The CAE model of deterioration category takes into account a number of parameters, which in mathematical sense corresponds to the components of the model vector

$$\left\{\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_N\right\} \qquad \text{... /Eq. 1/.}$$

When formulating the modeller of a phenomenon of categorisation $C = C(p_1, p_2, p_3, ..., p_L)$, it is assumed that one particular observation of the phenomenon can be described by a number of variables, which are regarded as components of a ***model vector***:

$$\mathbf{X} = \left\{p_1, p_2, p_3, ..., p_L, C\right\} \qquad \text{... /Eq. 2/.}$$

Vector **X** is composed of two truncated vectors:

$$\mathbf{P} = \left\{p_1, p_2, p_3, ...; \#\right\} \text{and } \mathbf{R} = \left\{\#; C\right\} \qquad \text{... /Eq. 3/,}$$

where # always denotes the missing portion. Vector **P** is complementary to the vector **R** and their concatenation will yield the complete model vector **X**. The problem to be solved is the estimation of the unknown complementary vector **R** by the given truncated vector **P** and by the model vectors$\{\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_N\}$. Using the conditional probability function the optimal estimator for the given problem can be expressed by:

$$r_k = \sum_{n=1}^{N} A_k \cdot r_{nk} \qquad \text{... /Eq. 4/}$$

where

$$A_k = \frac{a_n}{\sum_{j=1}^{N} a_j} \quad \text{and} \quad a_n = \exp\left[\frac{-\sum_{i=1}^{L}\left(p_i - p_{ni}\right)^2}{2w^2}\right] \qquad \text{... /Eq. 5/.}$$

Coefficient a_n can be written explicitly for both categorisation models, visual and test respectively. For example, expression

$$\exp\left[-\frac{(Pe-Pe_n)^2+(Cl-Cl_n)^2+(pH-pH_n)^2+(Ca-Ca_n)^2+(Ep-Ep_n)^2}{2w^2}\right] \text{... /Eq. 6/,}$$

stands for coefficient a_n in case of test model. Terms *Pe*, *Cl*, *pH*, *Ca*, *Ep* denote gas permeability, chloride ingress, alkalinity at the level of the reinforcement, carbonisation and electropotential parameters, respectively. In similar expression for visual model

$$\exp\left[-\frac{(Su-Su_n)^2+(Ds-Ds_n)^2+(Co-Co_n)^2+(Cr-Cr_n)^2+(Jo-Jo_n)^2+(Mo-Mo_n)^2}{2w^2}\right]$$

... /Eq. 7/,

Su, *Ds*, *Co*, *Cr*, *Jo*, *Mo* denote surface condition, scalling/delamination/spalling, corrosion, cracking, joints and moisture parameters, respectively. *w* is so called smoothing parameter.

The output parameter is the deterioration category, denoted as *C*. This result is a uniform variable which can have any value between 0.5 and 5.5. Individual deterioration categories have been determined by convention in the following ranges:

- category 1: 0.5 - 1.5 (mean 1.0),
- category 2: 1.5 - 2.5 (mean 2.0),
- category 3: 2.5 - 3.5 (mean 3.0),
- category 4: 3.5 - 4.5 (mean 4.0),
- category 5: 4.5 - 5.5 (mean 5.0).

4.3.3 Results

By CAE method the assessment results from different experts (team) can be presented either on a set of tables or on a set of simple diagrams, showing the iso-lines of equal deterioration or the boundaries between two deterioration categories. For better visual impression the results can be presented also as 3D-surface graphs.

In the following figures 1 typical results are presented for deterioration category based on visual data and on figures 2 for experimental data. The colours in the figures present the results in the vertical scale and are automatically generated for each picture, where the dark blue is the lowest category ("good condition") and dark red is the highest category ("the worst condition").

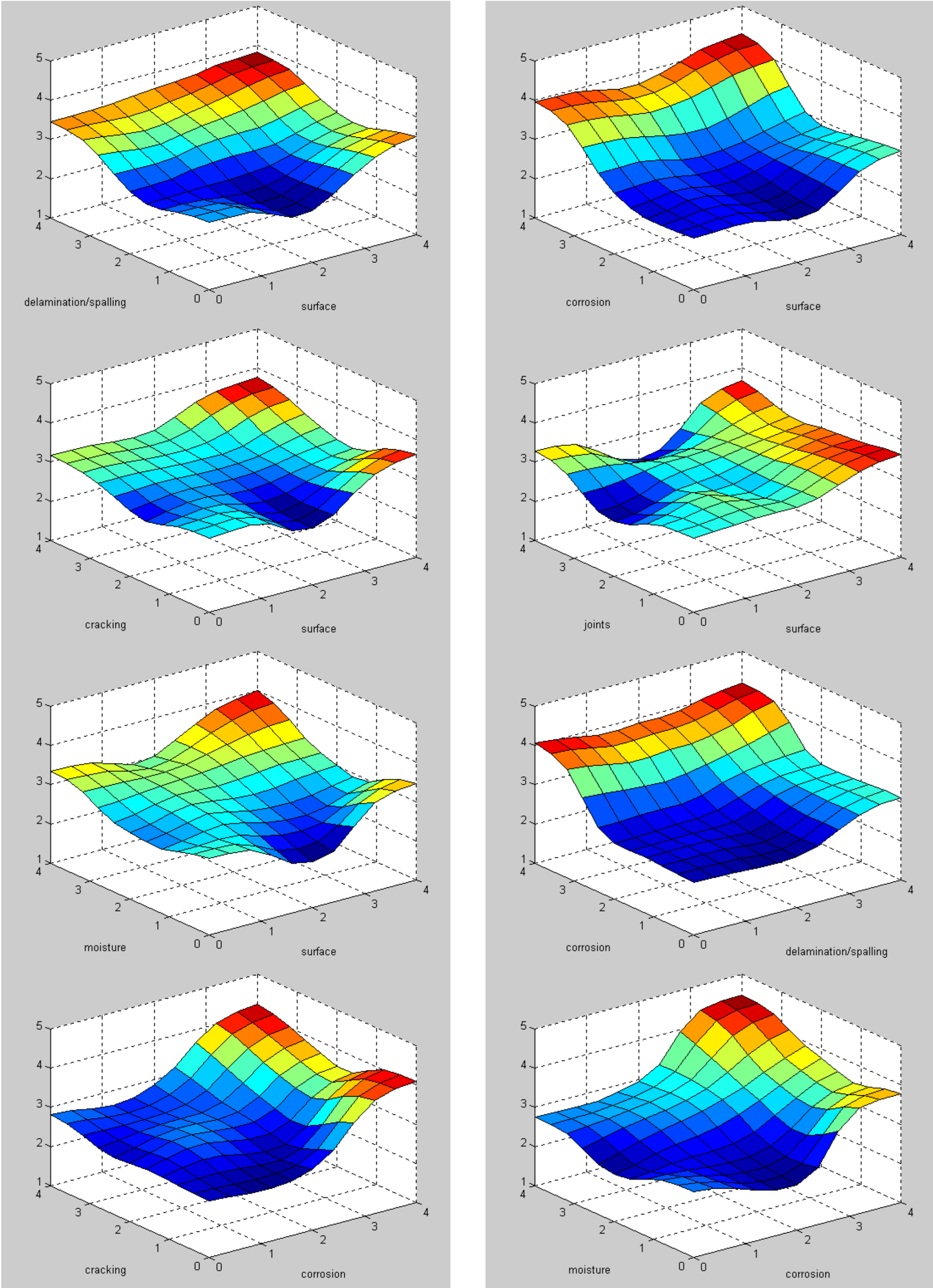

Figure 1: 3D presentations of deterioration category as a functions of two parameters - "visual model".

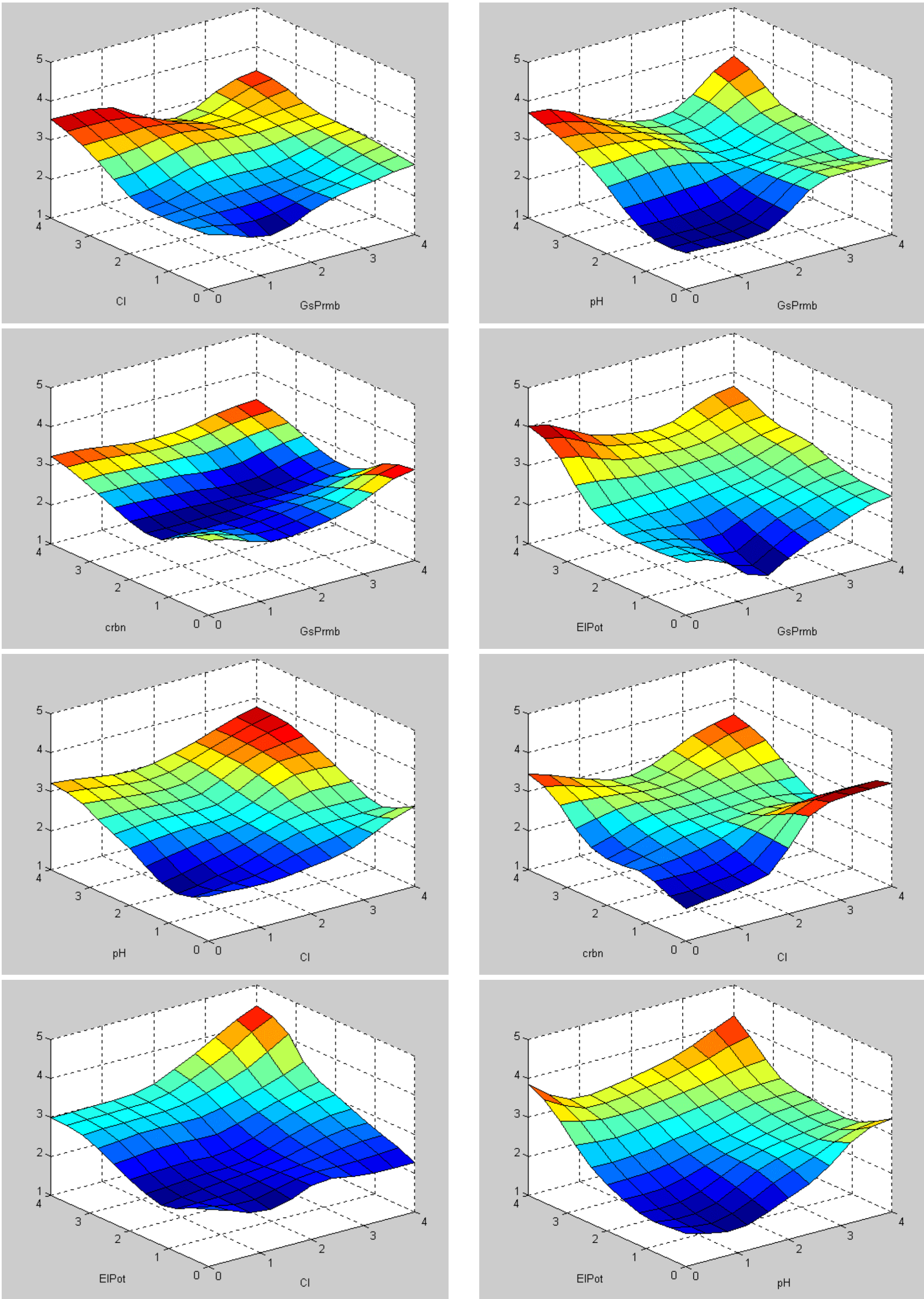

Figure 2: 3D presentations of deterioration category as a functions of two parameters – "experimental model".

A more detailed description of the model and a case study on a smaller sample of data is given in [3.2].

How can be this method used in practice and for what purposes?

The main purpose of using this method is to assess the damaged categories of large number of damaged locations on large structures. The first step is to make a mapping of all damaged locations and a visual assessment - visual categorisation. Based on this first visual categorisation a smaller number of damaged locations of each category are chosen, on which field measurements are carried out and samples are taken for laboratory tests. Based on these results an experimental categorisation is performed. By comparing the results of experimental and visual categorisation on selected damaged locations and how good they are matching, we can assess the change in percentages all other spots. By this final results a more reliable costs for repair work can be assessed if for each damaged category a corresponding repair work is described.

4.3.4 Example of categorisation using CAE NN

Data of one viaduct were selected to demonstrate the applicability of the model. Eleven locations were selected on which on-site measurements and laboratory measurements were carried out. The average concrete cover depth on the measured locations is 26.1 mm to the level of stirrups and 39.8 mm to the level of main reinforcement. The concrete cover depth to the post-tensioned ducts is about 52 mm. Results for visual categorisation are presented in table 3 and for test categorisation in table 4. In column BM are given the results for basic model, in column BM+Learn are given the results after the model was improved with additional learning. Through additional learning process a real categorisation was added to the database, which was evaluated after on-site measurements were finished. The results of visual categorisation for basic model show that of 11 locations 36% of them were put into category 1, 55% into category 3 and 9% into category 4.

TABLE 3: RESULTS OF VISUAL CATEGORISATION

Location	surface	delmn/ spall	corrosion	cracking	joints	moisture	BM	BM+Learn
1	1	2	1	0	0	3	2,50	3,22
2	1	2	2	0	0	3	2,50	3,81
3	1	3	2	0	0	4	3,00	3,98
4	1	0	0	0	0	1	1,00	1,19
5	2	3	2	0	0	4	2,75	3,99
6	1	3	2	1	0	3	3,00	3,89
7	1	0	0	0	0	2	1,33	1,68
8	1	3	1	0	0	2	3,00	3,92
9	1	0	0	0	0	1	1,00	1,19
10	1	0	1	0	0	1	1,00	1,67
11	1	0	0	3	0	2	3,50	1,50

TABLE 4: RESULTS OF TEST CATEGORISATION

Location	gas perm.	Cl	pH=reinf	Carbonat.	ElectPot	BM	BM+Learn
1	0	3	1	1	4	4,07	3,23
2	2	4	1	1	4	4,21	4,01
3	3	4	1	3	4	4,98	4,02
4	2	1	1	1	1	1,55	1,18
5	0	4	1	1	4	4,86	3,87
6	2	4	1	1	4	4,21	4,01
7	2	3	1	1	1	2,60	2,05
8	2	4	1	1	3	3,83	3,99
9	3	0	0	0	0	2,44	1,50
10	0	3	1	1	0	3,63	2,29
11	0	3	1	1	2	3,18	1,61

Comparison of these results with the results of basic model for test categorisation revealed that 75% of locations put in put into category 1 by visual categorisation will change into category 2 and 25 % into category 3. The analysis of locations, which were put into category 3 based on visual categorisation show that 67 % of these locations will change into category 4 and 33% into category 5. The analysis also shows that 25% of locations put into category 4 will change back to category 3. This result is primarily the consequence of experts' assessment of the influence the crack width has on the progress of corrosion reinforcement.

After the additional learning of the basic model, results (column BM+Learn) of visual categorisation changed with respect to the results of basic model and they comply quite well with results of test categorisation, which confirm the results of visual categorisation. Visual categorisation put 18% of 11 locations into category 1, 27% into category 2, 9% into category 3 and 46% into category 4. These results are finally applied to all damaged location on the structure.

In the following chapter a comparison of three methods, namely CAE, three layer BP NN (Back Propagation Neural Network, and ID3 on a simple data base of damage categorisation is presented.

4.3.5 Comparison CAE – three layer BP NN - ID3

CAE neural network was utilised for automatic (computerised) damage categorisation of deteriorated parts of the bridge. For the sake of simplicity and for discussion of applicability of both presented methods in this report, a very simple example on damage categorisation was made. Such damage categorisation is based on three input parameters only:

1. *Cl content at the depth of reinforcing (Cl^-),*
2. *depth of carbonisation (crbn) and*

3. cracks (crks)

Database consists of 10 samples (10 sample vectors or model vectors). Each input parameter has value in the range 0 - 4, while the final categorisation has value in the range 1 – 5 (same assumptions as for the actual model for damage categorisation described above).

Sample database:

No.	Cl^- *(% at cement weight)*	crbn *(depth in mm)*	crks *(class)**	category
1.	0.5	5	1	1
2.	1.2	0	3	5
3.	0.1	1	2	2
4.	0.1	10	1	2
5.	0.6	3	1	2
6.	0.0	15	3	3
7.	0.6	0	4	4
8.	0.2	3	4	5
9.	0.2	5	2	2
10.	0.1	2	1	1

*description of classes:
1. cracks at distances approx. 30 cm, opening less than 0.3 mm, dry
2. cracks at distances approx. 30 cm, opening less than 0.3 mm, wet
3. flexural cracks, opening more than 0.3 mm, dry
4. flexural cracks, opening more than 0.3 mm, wet

For comparison CAE with BP NN, the results presented in table 5 are for different *w* values. Results, which correpond to the training, are compared to the results of three layer BP NN (one hidden layer with six neurons).

TABLE 5: COMPARISON OF RESULTS OF CATEGORISATION FOR DIFFERENT METHODS

No.	**Cl^-** *(% at cement weight)*	**crbn** *(depth in mm)*	**crks** *(class)*	Category	**CAE** *w*=0.10	**CAE** *w*=0.15	**CAE** *w*=0.20	**BP NN**	**I.D.3**
1.	0.5	5	1	1	1.23	1.37	1.45	1.16	A
2.	1.2	0	3	5	5.00	5.00	4.99	4.93	C
3.	0.1	1	2	2	2.00	1.94	1.85	2.09	B
4.	0.1	10	1	2	2.00	1.99	1.92	2.02	B
5.	0.6	3	1	2	1.77	1.63	1.56	1.87	A
6.	0.0	15	3	3	3.00	3.00	3.00	3.01	B
7.	0.6	0	4	4	4.00	4.03	4.14	4.02	C
8.	0.2	3	4	5	5.00	4.97	4.85	4.94	C
9.	0.2	5	2	2	2.00	1.96	1.87	2.08	B
10.	0.1	2	1	1	1.00	1.11	1.31	1.02	A

As can be seen, the training results indicate a good prediction capability of both types of NN. Note, that the categories are defined as:

- category 1: 0.5 - 1.5
- category 2: 1.5 - 2.5
- category 3: 2.5 - 3.5
- category 4: 3.5 - 4.5
- category 5: above or equal 4.5

It should be noted, that ID3 results can not be directly compared to the results of NNs. Fair agreement of all three presented methods can be observed on this simple example. Reader interested in details, can find more results and comments in the appendices.

In the Appendix 1 a more detailed description of theoretical backgrounds for Neural Networks and Fuzzy logic, prepared by Dr.Lau Man Yick, is given.

5.0 CLASSIFICATION OF DEFECTS

5.1 General

Defects and deterioration on highway bridge structures can result from various factors, such as design, material, construction work, loading and environment. In reality, deterioration is usually caused by combinations of various factors that can lead to the functional, load carrying and long-term durability problems. Therefore, a reliable appraisal of defects and deterioration is very important for the evaluation of condition assessment of the structure, its load bearing capacity, remaining service life, functionality as well as for the design of appropriate repair strategy.

The cause for defects and deterioration due to design may result from:

- Inadequate specifications that were used at the time of design of the structure and later proved to be unsatisfactory.

- Inadequate detailing of specific parts of structure (e.g. the length of drain pipes under the bottom of the bridge deck surface are too short. In many cases they cause wetting and degradation of the concrete surface. Subsurfacing tubes, which drain collected water between bridge deck surfacing and waterproofing membrane, ends at the bottom level of the bridge deck, and the consequence is wetting and degradation of the concrete surface. Inadequate design of foundation protection in the riverbed may cause scour, which may result in fatal consequences, such as tilting, settlement or collapse of the supporting structure or even whole structure. Inadequate placing of the reinforcement may result in excessive cracks and deflections. Sometimes even collapse of the structure or its part can result from inadequate placing of the reinforcement. Inadequate design of concrete covers may lead to severe durability and load carrying problems if structure or its part is exposed to harsh global or micro-environment….).

The use of inadequate material can also lead to serious durability or load bearing problems. Defects and deterioration processes due to use inadequate material are the results of:

- Not known or not well understood properties of the used material at the time of construction (e.g. the use of different cement types in certain environmental conditions; the use of reactive aggregates can cause ASR and pop-outs; the use of aggregates containing high concentration of sulphides; the use of concrete additives which contain harmful substances to concrete; etc…).

- Poor quality control during the construction process (e.g.: placing of the concrete, which does not meet design requirements; the use of steel reinforcement in concrete structures or structural steel, which do not meet design requirements; etc…).

Defects may also result from construction work. One of the most widespread defects is inadequate concrete cover to the reinforcement. The evidence of this defect is not evident right away, but after some time due to visual signs of corrosion problems (rust stains) on the concrete surface. Sometimes the evidence is seen sooner on concrete surface in the form of the print of the reinforcement mesh due to colour variations caused by vibration. Some other defects due to construction works are: honeycombing due to poor compaction or aggregate grading; cracks induced due to differential settlement of the falsework; blow-holes due to air trapped against the formwork; etc….

Defects due to loading can have various forms. Excessive deflections of bridge decks can be the result of excessive loads under passing vehicles, for which the structure was not designed or the superstructure has deteriorated to such a stage that loading causes greater deflection than expected. Displacements of the abutments or retaining walls may be the result of greater earth-pressure, sometimes in the combination of undrained water behind the wall, or other causes, which may result in the global foundation instability. Due to impact or collision of vehicles, ships, or floating trees and ice severe defects may be induced on the substructure or superstructure of the bridges and other types of structure. Loading due to natural disasters such us flooding, earthquakes, landslides, rockfalls, fire in natural environment, etc… can also induce defects, which can be observed for many years after the event if the structure did not undergo a repair programme.

Environmental conditions, such as global climate conditions (e.g. coastal and continental regions, north-sea regions, polluted industrial regions, etc…) or micro-climate conditions (e.g. local wetting of the structure) can be the source of severe long-term deterioration processes and durability as well as load bearing problems of the structures.

Many types of defects and deterioration processes have characteristic visual traces on the exposed surface of the structures. During visual or in-depth inspection of structures such traces can give valuable information about defects themselves, their nature and cause. The time when traces become visible can varies from a few hours (e.g. plastic shrinkage and plastic settlement cracks in the concrete structures) to many years after the construction (e.g. long-term drying shrinkage cracks and cracks due to ASR in concrete structures; fatigue cracks in steel structures; rotting of the wooden structures; erosion of the riverbank slopes or riverbank protective structures or erosion of the highway structures along the flowing water; etc…). Therefore, it is essential for the reliable condition assessment to have records of initiation of defects and deterioration processes and their propagation from the beginning. As such records usually seldom exist for older structures, it would be advisable that for new structures such records are provided from the beginning of the construction phase.

5.2 Defects

Defects can be classified with respect to their main characteristic. If the main characteristic of defect is related to the different types of the element deformation, it can be classified as structurally related defect (deflection, buckling, tilting, etc…). If the main characteristic of defect is related to material properties, it can be related materially related defect (corrosion, delamination, etc.). Some defects can be classified as general, which may appear on all type of structures due to detailing, execution of work, weather, etc… Such defects are wetting, leakage, weathering, etc…

In the review of main defects those related to specific material characteristic are designated with the following symbols:

- **RC**: Reinforced Concrete,
- **PC**: Prestressed Concrete,
- **SS**: Structural Steel,
- **Al**: Aluminium,
- **CI**: Cast Iron,
- **WI**: Wrought Iron,
- **SM**: Stone Masonry,
- **BM**: Brick Masonry,
- **AP**: Asphalt pavement.

❖ Erosion

Erosion is the wearing away of soil by flowing water. This damage can be traced on the embankment and entrenchment slopes due to:

- ➢ heavy rainfalls (damage seen on greater surface area as many depressions oriented mainly downward),
- ➢ missing or damaged drainage on the embankment slopes (localised damage).

Erosion damages can be also seen on the riverbank slopes and riverbed bottom due to the actions of the speed water flow. Erosion damages can be also detected on riverbanks and riverbed protection structures, where parts or all elements of the protection structure were washed away.

❖ Abrasion

Abrasion is wearing away of the structure surface and can be caused by many factors. The most widespread causes are airborne or waterborne particles. The result is wearing away the surface of the material other than soil, which is rubbed by airborne or waterborne particles like sand, pebbles or stones. Damages caused by abrasion can be seen on the concrete (plain or reinforced), stone and brick masonry surfaces as well as wood structural elements. Damages due to abrasion can be traced on structural parts, which are in constant or occasional contact with flowing water or are exposed to strong winds. Abrasion can be also detected under the sewage or drainage pipes, which ends on the surfaces of retaining walls, abutments and wing walls, due to the flowing sewage or drained water with solid particles from the carriage-way. Abrasion damages can be also observed in the tunnels, if the leakage of high-flow rate water through joints or cracks is present. Damages due to abrasion can be sometimes seen also on substructures under the expansion joints without water-tightness membrane (e.g. finger type expansion joints), where most of the collected water is drained away over the abutment surface.

Friction forces due to ice formation or from moving ice can also cause abrasion. Very common cause of abrasion damage is collision of vehicles into the structures (e.g. collision of over-height vehicles into the superstructure).

- **Deformations**

Deformation is a general term, which indicates that structural element exhibit a shape other than it had it in the initial phase of construction. For main structural elements characteristic deformation shapes have special meaning, such as deflection is a vertical movement of the superstructure elements, while vertical movements as such, lateral and rotational movements are related to the deformations of the supporting structures.

Deformations have a variety causes, such as: inadequate fabrication of the prefabricated elements or inadequate erection, lack of adequate joints between elements, use of material with inadequate mechanical characteristics, torsional effects not taken into account in the design, missing connectors between elements (e.g. rivets, bolts of steel structures), inadequate bracing. Deformations are caused by loading, such as self-load, impact load, temperature, earth pressure, etc…

Local deformations of the elements due to different causes are:

- **Buckling:** inelastic change of the alignment of the element due to compression forces or stresses. It is usually observed in steel structures.

- **Mechanical damage:** local change of the shape of the element. It is usually related to the impact forces due to collision of vehicles into the structure. It can be observed on all structural elements along the carriageway. The worst condition of the mechanical damage is **broken element**, which means that element is locally completely disintegrated.

- **Distortion:** This type of defect is usually associated with deformations of masonry structures like sagging and warping. It is also often related to the bearings, especially for reinforced and unreinforced elastomeric bearings. At some bearings additional to the horizontal and vertical deformations a torsional deformation around vertical axes can be observed.

☆ **Deflections**

Excessive deflections of the superstructure can be caused by loads and/or creep. It can be traced by periodical measurements of deflections. Visible signs like sagging in the middle of the span and ponding usually indicate the problems with excessive deflections. When the structure is made of reinforced concrete, flexural cracks will generally occur on the superstructure.

☆ **Movements**

Vertical movement (settlement or displacement) of the supporting structures (abutments, wing walls, retaining walls, piers) may be caused by various reasons, like errors in the foundation design assumptions or design of the structural elements of the foundations (e.g. piles and pile caps, strip foundations on flexible soil with local inclusions of rocks). Settlements can be uniform or differential, of which latter is far more serious. Settlement of the bridge approach slabs induce dynamic effect on the passing vehicles and indirectly to the superstructure.

Lateral movements can be caused by a foundation soil or slope failure, additional water pressure due to undrained water behind the wall (abutments, retaining walls) or by changes in the soil characteristics and consolidation of the original soil.

Rotational movement is usually the result of unsymmetrical settlements or lateral movements.

Special types of movements can be observed on the spandrel wall of brick and stone masonry as well as concrete bridge structures. These transverse horizontal movements, like **tilting**, **bulging,** and **sliding** of the spandrel wall are mainly the consequence of the interaction between the barrel, spandrel wall, lateral soil pressure and impact of heavy traffic.

Excessive horizontal and rotational movements can be also observed on the bearings. Seriousness of the movements depends on bearing types.

❖ **Scour**

Scour is erosion of a foundation soil in the river bed under or at the foundations of the supporting structures like abutments, retaining walls, piers, columns.

❖ **Weathering**

Weathering of the structure's surface is the result of action of air pollution, frost, rain and sunlight. The appearance of structure surface is affected.

- **Wetting**

Wetting of structure surface is caused by many factors. It can cause a serious damage in concrete and steel structures, if water, which is a cause for wetting, is contaminated with salts. Constant wetting can cause serious damages also in wooden structures (rotting, fungi, etc…). Wetting of the porous structure surface can also help to form freeze thaw damage.

- **Leakage**

Leakage of water occur when water find a way to penetrate through the structural element and visible traces of wetting surface become visible on the opposite side (e.g. spots of wetting on the underside of the bridge deck). It can occur all type of superstructure as well as on the retaining walls, abutments, wing walls, tunnels and galleries.

- **Efflorescence**

Efflorescence is deposit of white salts caused by crystallisation of soluble salts brought to the surface by moisture. It can be traced on concrete and brick and stone masonry. On steel structures efflorescence can be observed only if concrete, stone or brick masonry deck is supported by steel elements.

- **Vegetation**

On the structures, made of concrete, brick and stone masonry vegetation like moss, grass, small trees can start to grow. Moss and grass tend to trap moisture at the surface, causing that surface pores remain saturated even in dry conditions. Roots of small plants tend to disintegrate concrete surface and widen cracks and joints in the brick and stone masonry structures.

- **Freeze Thaw damage**

Freeze thaw damage occurs due to cycle actions of freeze and thaw. The main reason is expansive pressure generated by freezing of trapped water in materials pores or capillaries. The visible traces of deterioration due to freeze thaw are surface scaling or disintegrated surface to the depth to which freezing condition have penetrated. Freeze thaw damages can be observed on concrete and brisk and stone masonry. More severe freeze thaw damages are caused in the presence of de-icing salts. Due to application of de-icing salts, a sudden drop of the temperature on the surface during thawing induce internal stresses in the outer layers causing disintegration of the surface.

❖ Cracking (RC, PC)

Cracks have various shapes and causes, depending they are induced by loading, rheology or by deterioration. Cracking is a break of a structural element without complete separation of the element. Cracks and crack patterns have different characteristics depending on the cause of cracking. In essence, there are two types of cracking: Structural and non-structural types of cracking. Non-structural type of cracks can form before hardening (early frost damage, plastic shrinkage and plastic settlement, constructional movement – formwork or sub-grade movement) or after hardening of the concrete (e.g.: drying shrinkage, crazing, corrosion of the reinforcement, freeze thaw cycling, temperature, alkali-aggregate reactions). Structural cracks can form due to design load level, overloading and creep.

❖ Reinforcement Corrosion (RC, PC)

Corrosion is a deterioration process of steel by electrolysis or chemical attack, at which steel cross section reduces locally or uniformly. Corrosion characteristics differ depending on the main cause of corrosion. Carbonation is source of corrosion process, at which carbon dioxide reacts with the calcium hydroxide in the cement paste. The consequence is the reduction of the alkaline environment of pH from about 12,5 to about 9,0 and break down of the alkaline environment. Another cause of severe corrosion is penetration of chlorides into the concrete. Carbonation induced corrosion tends to be more general, though localised corrosion can occur on isolated bars with low concrete cover. Chloride induced corrosion is characterised by local and rapidly corroding areas.

✰ *Ordinary reinforcement*

The corrosion of reinforcement starts very quickly, if the reinforcement is directly exposed to the atmosphere (e.g. reinforcement in the honeycombing). The corrosion process is slow if other aggressive substances are not present. In the first stage of corrosion processes there are no visible traces on the concrete surface, but after some time rust stains and later cracking spalling and delamination become visible signs of undergoing process.

✰ *Prestressing reinforcement*

Corrosion of the prestressed reinforcement can also starts if prestressed reinforcement is exposed to the air humidity (e.g. the joints between precast segments, which were not adequately sealed), or due to carbonation of the concrete and penetration of the chlorides into the concrete, if concrete cover depth was too small. Corrosion due to chlorides can also starts in ungrouted ducts, if contaminated water has found path into the duct through the unprotected anchorages or some other sources. Prestressed reinforcement can break due to stress corrosion or hydrogen embrittlement.

- **Honeycombing (RC, PC)**

  Honeycombing is a typical defect of concrete or prestressed concrete structure due to inadequate grading and/or poor compaction, which result in segregation of coarse aggregates from the fine aggregates and cement paste.

- **Inadequate concrete cover (RC, PC)**

  Inadequate concrete cover is immanent defect of concrete structures. It can occur during the design or construction phase. It is rarely visible right away. It can be detected by NDT measurements of concrete cover depth.

- **Scaling (RC, PC)**

  Scaling is gradual and continuous loss of structural surface.

- **Spalling (RC, PC)**

  Spalling is local depression in the structure surface. It can be caused by corroding reinforcement or friction due to thermal movement. Reinforcing steel is often exposed.

- **Delamination (RC, PC)**

  Delamination occur in concrete structures, when concrete layers separate at or near the outermost layer of the reinforcing steel. It is caused bay corrosion of the reinforcement. It usually occur when bars are closely spaced and/or reinforcing bars are placed deeper under the surface.

- **Disintegration (RC, PC)**

  Disintegration of concrete is a deterioration process, at which concrete deteriorate into small fragments due to factors such as weathering, corrosion, erosion and chemical attack. It is usually observed on secondary elements, such as concrete curbs, sidewalk, etc…

- **Alkali-silica reaction – ASR (RC, PC)**

  Alkali-silica reaction occurs when alkaline pore water in the cement paste reacts with the minerals in some aggregates to form a calcium alkali-silicate gel. This gel takes up pore solution water and expands, which can disrupt the concrete. The signs of ASR deterioration may become visible after many years since construction in the form of typical crack pattern.

- **Breaking-away of the concrete (RC, PC)**

Breaking-away of the concrete is usually the consequence of the impact forces or due to temperature effects, when two adjacent elements are too close together without adequately designed joint.

- **Damage of concrete surface protective coatings – paint (RC, PC)**

Due to inadequate application, ageing, salt crystallisation, weathering, etc… damages can be observed on the coating membrane. Damages have various shapes, like cracking, peeling, blisterings, etc…

- **Damage of concrete surface mortar coatings (RC, PC)**

Some parts of the concrete structures, like abutments, piers and retaining walls have sometimes additional coating made of cement mortar. Due to ageing, temperature and other effects the mortar tend to crack, disintegrate and spall.

- **Fatigue and fracture cracking (SS, Al, CI, WI)**

In steel and aluminium structures a fatigue cracks can develop due to repeated stresses. These cracks propagate slowly in the initial phase. If such cracks are not treated on time, they frequently initiate brittle fracture. Another type of cracking is fracture cracking caused by low temperature, stress or strain concentration or metallurgical composition. Fracture cracks are brittle that takes place with little or no preceding plastic deformation.

Fracture cracking may be caused due to stress or strain concentrations, low temperature or metallurgical composition. By its nature it is a brittle one with little or no preceding plastic deformation. They are often triggered by sudden increase in load.

- **Corrosion (SS, Al, CI, WI)**

Corrosion of the steel and connecting devices has many different types. The main types of corrosion are:

- Environmental corrosion, which primarily affects metal in the contact with soil or water, especially if the water is sea water or contaminated with de-icing salts.
- Stray current corrosion is primarily caused by the vicinity of electric railway.
- Bacteriological corrosion can be induced by organisms found in swamps, stagnant waters, clay, etc…

Pitting corrosion can be observed on the aluminium structures, but it rarely become serious.

- **Damage of coatings for corrosion protection (SS)**

Due to inadequate application, ageing, weathering, etc… damages can be observed on the steel corrosion protection coatings. Damages have various shapes, like cracking, peeling, blisterings, etc…

- **Damaged or missing connecting devices (SS, Al, CI, WI)**

Connected devices such as rivets and bolts may be damaged due to induced loads, corrosion, dynamic actions. They can fell off from their position. Sometimes They are forgotten to be placed into position. Cracks may be observed in the welds.

- **Scaling (SM, BM)**

Scaling is gradual and continuous loss of structural surface, which can be of stone or brick masonry.

- **Spalling** (SM,BM)

Spalling is local depression in the structure surface. It is a condition where outer layers of masonry units begin to break off in parallel layers from the larger blocks of masonry.

- **Delamination (SM, BM)**

Delamination is observed, when outer surface of the masonry splits into thin layers and peels off the masonry surface.

- **Falling-out of masonry units (SM, BM)**

This type of damage is observed, when masonry units fall out of structural elements due to disintegration of the mortar, deflections, settlement, etc….

- **Cracking (SM, BM)**

Crack in brick and stone masonry can have various forms, shapes and causes. They are usually related to global deformations (settlement, tilting, buckling) or loading. Very common shape of the crack is longitudinal crack between spandrel wall and arch barrel of bridge structures. Due to loss of mechanical bond between adjacent rings cracks can occurs as a consequence of ring separation. Splitting cracks can occur due to temperature changes, frost and freezing. They can form through the mortar joints and masonry units.

- **Friability (SM)**

It is a characteristic of some stone types, like sandstone or limestone. They have a tendency to crumble, break up or powder.

- **Disintegration of the mortar (SM, BM)**

  Due to ageing, weathering, temperature, moisture, freeze and thaw, chemical reactions, etc… mortar disintegrates in the joints. The consequence may be falling out of masonry units, deformations of the structure, etc…

- **Detachment (SM, BM)**

  This type of damage is a result of complete break in a masonry unit in which detached portion of masonry unit is intact. Sometimes it is a result of a failure of an original construction joint.

- **Corrosion of metal mechanical connectors (SM, BM)**

  Due to presence of moisture, de-icing salts corrosion of the metal connectors may be observed on masonry structures. The break of the ties may cause severe deformations of the superstructure.

- **Peeling of the masonry cover mortar (SM, BM)**

  Some masonry structures have a layer of mortar coating. Due to ageing, temperature, moisture and other effects the mortar tends to peel off the masonry surface.

- **Cracking (AP)**

  Cracking in the pavement have various causes, among the most common are temperature changes, shrinkage, dynamic loading, hidden discontinuities and settlement in the sub-soil. Cracks have various forms. The most common are longitudinal, transversal and alligator like cracks.

- **Dropping out of aggregates (AP)**

  Due to poor binding material and weathering grains are dropping out of the asphalt matrix under the loading.

- **Wheel tracks (AP)**

  Due to high wheel loads and ageing of the pavement or poor quality of the pavement construction wheel tracks can occur along the driving lines.

- **Deterioration of the waterproofing membrane**

Deterioration of the waterproofing membrane is caused by using inadequate material, carrying out the work under inadequate weather and temperature conditions, application on inadequate prepared surface, as well as wheel and temperature loading.

- **Inadequate detailing of the waterproofing membrane**

Due to inadequate detailing of the waterproofing membrane around specific elements, such as drainage pipes or pipes for pressure release, leakage around such elements may cause local severe deterioration problems.

- **Disintegration of the joint mortar**

Due to weathering, temperature and loading effect mortar in the joints among curb elements or curb elements and sidewalk disintegrate in course of time.

- **Deterioration of elastic sealant**

Sealant tend to deteriorates due to poor resistance to weathering, inadequate adhesion to the subsurface, ageing, etc… The visual signs of deterioration are initiation of cracks and crack propagation and material disintegration. Usually from the joints with deteriorated sealant vegetation start to grow.

- **Damage on bridge structures equipment**

Damages on highway structures equipment are related to the loading and deterioration process of the basic material they are made of. Due to the loading the damage can be described as: warping, broken, missing, displaced, tilt.

Damages of the equipment made of concrete (safety barriers, curbs, slope drainage elements, etc…) due to deterioration can be usually described as disintegration and cracking of the concrete with or without corroded reinforcement.

Fixing bolts of the expansion joints, bearings, sign gantries, safety barriers, etc., can be corroded or damaged due to load effects or corrosion. Sometimes fixing elements are missing.

Steel elements can exhibit deterioration of the steel due to corrosion or deterioration of the steel corrosion protection.

Rubber surface of the rubber expansion joints usually has scars on the surface induced by plough during the winter times.

Plastic glass used for noise protection can exhibit local damages due to impact of sands during the ploughing in the winter.

- **Damages caused by vandalism**

The most frequent damages caused by vandalism are graffiti, broken sign posts, broken lamps, broken drainage pipes and stolen elements, such as embankments slope protection elements.

6.0 GUIDELINES FOR CONDITION ASSESSMENT

Condition assessment (CA) of bridge structures provides the owner or the authorities responsible for maintenance with an appraisal of the present condition of the structures. Assessment should give data on the intensity and extent of visible defects on the structures, their cause and possible deterioration processes, and the impact of such findings on the safety and service life of the structures. Such data are the basis for the estimation of possible intervention and for providing an estimate of the costs of possible remedial work.

Assessment is not always an easy task. Sometimes deterioration processes have several causes and it is difficult to find the basic causes and an explanation and understanding of the problems. Only when the problems are well defined and understandable can a reliable treatment of the defects be efficiently proposed and executed.

Therefore, the main objectives of the CA are:

- Detect possible deterioration processes,
- Indicate the condition of the bridge and its elements as well as the bridge stock,
- Rank bridges in terms of their need for urgent repair and maintenance,
- Optimise the budget for urgent maintenance.

To trace the progress of deterioration processes of a structure with respect to the lifetime of the structure, defects should be graded with respect to their intensity and extent. Gradation should be made in a manner that is suitable for the damage type, its cause and the material the structural element is made of (e.g.: cracks in reinforced or prestressed concrete, brick or stone masonry). It is important that as many as possible of the defects, which have an impact on condition, functionality, durability and load bearing capacity are included in the catalogue of defects. Such a catalogue helps the inspector along with their engineering judgement and experience to make a reliable assessment of defects and deterioration processes, their cause and possible propagation in the future.

To obtain valuable data for the evaluation of condition assessment and ensure that the results of condition assessment can be properly and effectively used in further analysis, a few basic requirements should be fulfilled, such as:

- Structures must be inspected regularly at properly determined time intervals from the beginning of a structure, i.e. when the structure is put into service or after every major repair work is carried out.
- Different levels of inspections must be executed with adequate trained and educated personnel as well as using suitable equipment.
- Some defects may have been introduced during the construction of a structure. Therefore, a knowledge of the history of problems that occurred during construction may be very helpful in the condition assessment.
- A catalogue of defined defects, deterioration processes and their possible causes should be available.
- Well-defined methods for quantification of defects with respect to their intensity and extent as well as their possible impact on the users safety and durability of the structural elements.

Evaluation of every damage type should account for:

- The type of damage and its affect on the safety and/or durability of the affected structural member.
- Effect of the affected structural member on the safety and durability of the whole structure (e.g. bridge) or structural component (e.g. span structure of a bridge).
- Maximum intensity of any defects on the inspected members.
- Extent and expected propagation of the damage on the observed members within a component.

Experience and knowledge gained through the execution of inspections, evaluation of condition assessment as well as further analysis of the results of condition assessment have an impact on the development of new procedures for condition assessment or improving the existing ones. The result is that procedures for condition assessment as well as the methods for quantification of the condition assessment are changing.

Assessment of deteriorated structures is a very important task and must therefore be carried out by experienced engineers. Assessment of structures is always a combination of a predefined assessment method and engineering judgement. Some subjectivity is always part of engineering judgement of structural condition. To reduce subjectivity in the assessment as much as possible, continuous education is needed as well as periodic improvements to the catalogue of defects and methods for quantification of defects.

7.0 CONCLUSIONS

Assessment of deteriorated structures is a very important task and must therefore be carried out by experienced engineers. Assessment of a structure is always a combination of pre-defined assessment method and engineering judgement. Some subjectivity is always included in the engineering judgement element of a structural condition assessment. To minimise subjectivity in the assessment continuous education is needed as well as periodic improvements to the catalogue of defects and methods for quantification of defects.

Probabilistic methods and new mathematical methods such as neural networks and fuzzy logic have been introduced for the assessment of deteriorated locations of structures with the aim of minimising the subjectivity of engineering judgement. These methods are increasingly used in further analysis of condition assessment data, i.e. prediction of deterioration rate and optimisation of maintenance procedures.

Future research is needed in order to find a way to introduce these methods to the assessment of highway structures.

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Appendix 1

COMPARISON OF 3 METHODS OF DAMAGE CATEGORISATION (NEURAL NETWORK, CAE and ID3)

(Prepared by Dr.Lau Man Yick)

AI-1 Neural Networks

AI-1 Introduction

Soft computing, a branch of soft science, consists of several computing paradigms, including fuzzy set theory (knowledge representation via fuzzy IF – THEN rules), neural network (learning and adaptation) and genetic algorithm and / or simulated annealing (Derivative – free optimisation, systematic random search). All biological neural functions, including memory, are stored in the neurons (approximately 10^{11}) and in the connections (approximately 10^{4} per neuron) between them by the junctions of the synapse.

The relation between biological neurons and artificial neurons is presented in Fig 1-1, Fig 1-2 and Fig 1-3.

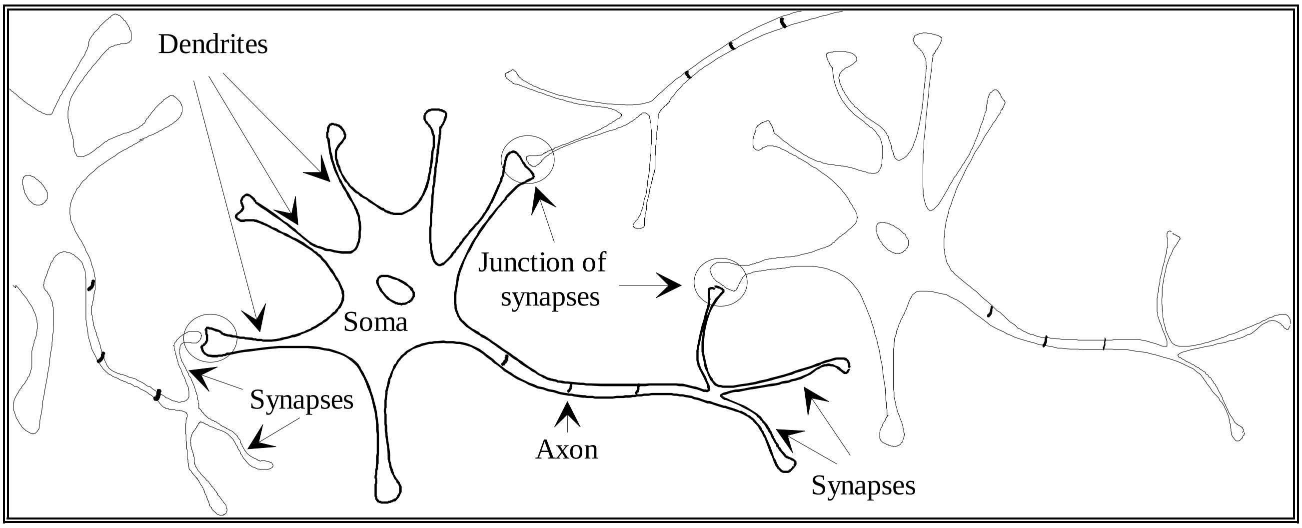

Fig 1-1 Biological neurons (Number of neurons $\cong 10^{11}$)

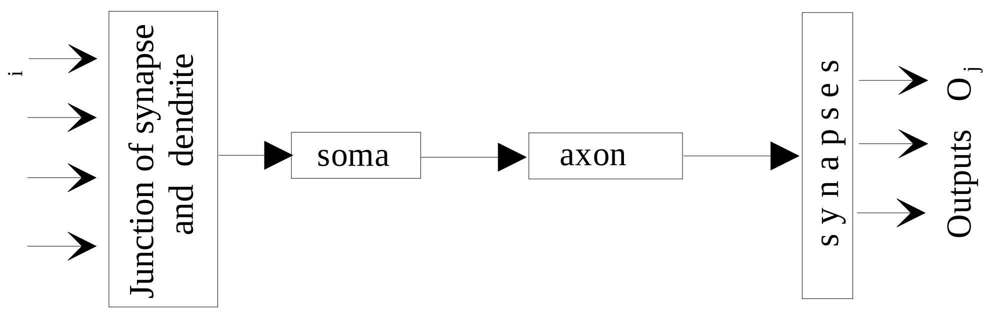

Fig 1-2 Schematic presentation of neuron

Junction **<u>Synaptic</u>**	**Soma** **<u>Somatic Operation</u>** **(treatment of information)**	**Axon** **<u>Transport of information</u>**	**Synapses** **<u>Transmission</u>**
• Receive information O_i coming from another neurons	• Space - temporal operation of aggregation (operation of confluent) $net_j = \sum_i W_{ji} O_i \quad , \quad i \cong 10^4$		• Transmit information O_j to another neurons
• Supply the weight W_{ji} to neurons O_i (Storage of knowledge already acquired $W_{ji} \rightarrow$ long term cumulative memory)	• Activate function (linear or non linear) $O_j = f(net_j - \theta_j)$ θ_j : Activate Threshold of neuron i		

Fig 1-3 Physical and mathematical explanations

The neuron networks began in the 1940s with the work of WARREN McCULLOCH and WALTER PITTS, who showed that neuron networks could compute any arithmetic or logical function.

In this field DONALD HEBB, FRANK ROSENBLATT, BERNARD WIDROW, TED HOFF, SEYMOUR PAPERT, TEUVO KOHONEN, JAMES ANDERSON and STEPHEN GROSSBERG have given a lot of contribution.

Neural networks can be applied in many field: aerospace, defence, automobile, robotics transportation even in the securities, banking financial, medical, telecommunication etc.

The neuron networks can be divided into two parts: static and dynamic. We discuss only in the domain of static which can also be separated in classification and parsimonious approximation of a non linear function.

Each neuron is a process unit. All the neurons are adaptive by the learning rule, which means the outputs of these neurons O_j depend on modifiable weight of synapse W_{ji} including in the operation of aggregation net_j and activate thresholds θ_j.

The definition of the supervised learning rule is the modification of the Weight of synapse W_{ji} between neurons using a set of input – output (targets) samples, after learning , a new input element can be correctly classed. The detail is developed in next section.

I-2 Back - propagation learning rule with a momentum term

Back -propagation is a learning rule for adaptive multiple - layer networks, which is a simple steepest descent method. Input vectors and corresponding output vectors are used to train a network until it can approximate any function or classify input vectors in group. The performance index of this method is mean square error.

So let it be a three layers network (Fig 1-4) :

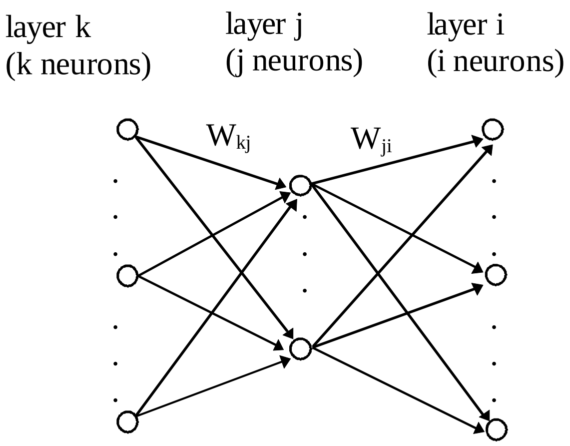

Fig 1-4 Three layers network

- input layer k
- hidden layer j (one hidden layer is sufficient for any non linear universal approximation)
- output layer i
- k, j, i are also the number of the neurons in each layer
- The correction of the error from layer i until layer k
- The connection between the neurons (Fig 1-5) is from left (layer k) to right (layer i).

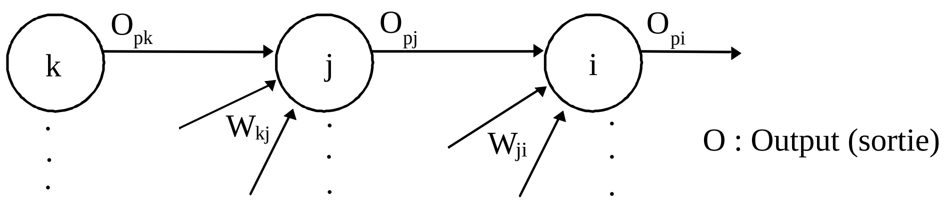

Fig 1-5 Connection between the neurons

- Net (NET - ACTIVATION) is the effect of previous layer's neurons to the neuron of the next layer.

where $O_{pi} = f(net_{pi}) = \dfrac{1}{1 + \exp(-net_{pi})}$ (1-1)

$$O_{pj} = f(net_{pj}) = \frac{1}{1 + \exp(-net_{pj})} \qquad (1\text{-}2)$$

f : Log - Sigmoid (the other possible transfer functions : Hyperbolic Tangent Sigmoid, competitive...)

p : Stimulus (p=1) or stimuli (p>1)
O_{pi} and O_{pj} are the outputs of the transfer functions.

$$O_{pi} = f(net_{pi}) = \tanh(net_{pi}) \qquad (1\text{-}3)$$

The derivative of the Log - Sigmoid functions are :

$$\frac{d\,O_{pi}}{d\,net_{pi}} = O_{pi}(1 - O_{pi}) \qquad (1\text{-}4)$$

W_{kj} : Intensity of the connection between the k^{th} neuron of the k^{th} layer and the j^{th} neuron of j^{th} layer (modifiable synapse weight)

W_{ji} : Intensity of the connection between j^{th} neuron of the j^{th} layer and the i^{th} neuron of the i^{th} layer.

$$net_{pi} = \sum_j W_{ji} O_{pj} - \theta_i \qquad (1\text{-}5)$$

et

$$net_{pj} = \sum_k W_{kj} O_{pk} - \theta j \qquad (1\text{-}6)$$

θ_i, θ_j : Threshold

The least Mean Square (LMS) learning procedure or WIDROW-HOFF learning rule can give the correct values of W_{kj} and W_{ji}

the global error of the system are defined as the following :

$$E_p = \frac{1}{2}\sum_i \left(d_{p_i} - O_{p_i}\right)^2 \qquad (1\text{-}7)$$

$$E = \sum_p E_p \qquad (1\text{-}8)$$

p : the number of stimuli (number of element in database)

d_{pi} : Theory reply or target of the i^{th} output neuron under stimulus p.

O_{pi} : reply of the i^{th} neuron of the output under stimulus p.

Correction de W_{ji} between HIDDEN LAYER and OUTPUT LAYER.

The variation of error owing W_{ji} :

$$\frac{\partial E_p}{\partial W_{ji}} = \frac{\partial E}{\partial O_{pi}} \frac{\partial O_{pi}}{\partial net_{pi}} \frac{dnet_{pi}}{dW_{ji}} \qquad (1\text{-}9)$$

Utilising the formulas (1-7),(1-1)and (1-5), we obtain :

$$\frac{\partial E_p}{\partial W_{ji}} = -\left(d_{pi} - O_{pi}\right)\left[O_{pi}\left(1 - O_{pi}\right)\right]O_{pj} \qquad (1\text{-}10)$$

Introducing (1-10) to (1-7) and then (1-7) to (1-8) we can obtain the global error of all neurons i and the global error of stimuli.

The learning rule (Estimation of the parameters) of w_{ji}^{n} :

$$W_{ji}^{n+1} = W_{ji}^{n} + \Delta W_{ji}^{n} \qquad (1\text{-}11)$$

(n : n^{th} loop of calculation)
and

$$\Delta W_{ji}^{n} = -\eta \frac{\partial E}{\partial W_{ji}} \quad ; \quad \eta > 0 \qquad (1\text{-}12)$$

where η is the running rate [0.25 - 0.50]
then

$$\Delta W_{ji}^{n} = \eta\left\{\left(d_{pi} - O_{pi}\right)\left[O_{pi}\left(1 - O_{pi}\right)\right]O_{pj}\right\} \qquad (1\text{-}13)$$

$$= \eta\left\{\delta_{pi} O_{pj}\right\} \qquad (1\text{-}14)$$

where

$$\delta_{pi} = \left(d_{pi} - O_{pi}\right)O_{pi}\left(1 - O_{pi}\right) \qquad (1\text{-}15)$$

or $$\delta_{pi} = \left(d_{pi} - O_{pi}\right)f'\left(net_{pi}\right) \qquad (1\text{-}16)$$

η : length of the step calculated.

The variation of error owing θ_i:

$$\frac{\partial E_p}{\partial \theta_i} = \frac{\partial E_p}{\partial O_{pi}} \frac{\partial O_{pi}}{\partial net_{pi}} \frac{dnet_{pi}}{d\theta_i} \tag{1-17}$$

we find :

$$\frac{\partial E_p}{\partial \theta_i} = \left(d_{pi} - O_{pi}\right) O_{pi} \left(1 - O_{pi}\right) \tag{1-18}$$

$$\because \frac{dnet_{pi}}{d\theta_i} = -1$$

The learning rule of θ_i:

$$\theta_i^{n+1} = \theta_i^n + \Delta\theta_i \tag{1-19}$$

$$\Delta\theta_i = -\eta \frac{\partial E}{\partial \theta_i} \tag{1-20}$$

$$\Delta\theta_i = -\eta \quad \delta_{pi} \tag{1-21}$$

Correction of W_{kj} between INPUT LAYER and HIDDEN LAYER

The variation of error owing W_{kj}:

$$\frac{\partial E_p}{\partial W_{kj}} = \sum_i \left(\frac{\partial E_p}{\partial O_{pi}} \frac{\partial O_{pi}}{\partial net_{pi}} \frac{\partial net_{pi}}{\partial O_{pj}} \right) \frac{\partial O_{pj}}{\partial net_{pj}} \frac{dnet_{pj}}{dW_{kj}}$$

$$= -\sum_i \left\{ \left(d_{pi} - O_{pi}\right) \left[O_{pi} \left(1 - O_{pi}\right) W_{ji} \right] \right\} \left[O_{pj} \left(1 - O_{pj}\right) \right] O_{pk}$$

$$= -\sum_i \left\{ \left(d_{pi} - O_{pi}\right) \left[O_{pi} \left(1 - O_{pi}\right) \right] O_{pj} W_{ji} \right\} \left(1 - O_{pj}\right) O_{pk} \tag{1-22}$$

Introduce (1-10) to (1-22) we obtain:

$$\frac{\partial E_p}{\partial W_{kj}} = \left(\sum_i \frac{\partial E_p}{\partial W_{ji}} W_{ji} \right) \left(1 - O_{pj}\right) O_{pk} \tag{1-23}$$

The learning rule of w_{kj} :

$$W_{kj}^{n+1} = W_{kj}^{n} + \Delta W_{kj} \tag{1-24}$$

and,

$$\Delta W_{kj} = -\eta \frac{\partial E_p}{\partial W_{kj}}$$

$$= -\eta \left[\sum_i \left(\frac{\partial E_p}{\partial W_{ji}} W_{ji} \right) \left(1 - O_{pj}\right) O_{pk} \right]$$

$$= \sum_i \left(\Delta W_{ji} W_{ji} \right) \left(1 - O_{pj}\right) O_{pk} \tag{1-25}$$

We can also write ΔW_{kj} in the flowing way :

$$\Delta W_{kj} = -\eta \frac{\partial E_p}{\partial W_{kj}}$$

$$= \eta \delta_{pj} O_{pk} \tag{1-26}$$

where

$$\delta_{pj} = -\sum_i \left(\frac{\partial E_p}{\partial W_{ji}} W_{ji} \right) \left(1 - O_{pj}\right)$$

$$= -\sum_i \left[-\left(d_{pi} - O_{pi}\right) O_{pi} \left(1 - O_{pi}\right) O_{pj} . W_{ji} \left(1 - O_{pj}\right) \right]$$

$$= \sum_i \left\{ \left(d_{pi} - O_{pi}\right) O_{pi} \left(1 - O_{pi}\right) \right\} W_{ji} O_{pj} \left(1 - O_{pj}\right)$$

$$= \sum_i \left\{ \left(d_{pi} - O_{pi}\right) O_{pi} \left(1 - O_{pi}\right) \right\} W_{ji} f © \left(net_{pj}\right) \tag{1-27}$$

with formula (1-15) we write :

$$\delta_{pj} = \sum_i \left\{ \delta_{pi} W_{ji} \right\} f © \left(net_{pj}\right) \tag{1-28}$$

The learning rule of θ_j :

$$\theta_j^{n+1} = \theta_j^n + \Delta\theta_j \tag{1-29}$$

and

$$\Delta\theta_j = -\eta \frac{\partial E}{\partial \theta_j} \tag{1-30}$$

where

$$\frac{\partial E}{\partial \theta_j} = \sum_i \left(\frac{\partial E}{\partial O_{pi}} \frac{\partial O_{pi}}{\partial net_{pi}} \frac{\partial net_{pi}}{\partial O_{pj}} \right) \frac{\partial O_{pj}}{\partial net_{pj}} \frac{dnet_{pj}}{d\theta_j} \tag{1-31}$$

$$\Delta\,\theta_j = -\eta \quad \delta_{pj} \tag{1-32}$$

Remarks :

1) This method is also valid for n layers

2) For the reason of fast convergence, we always use big η, but this provoke oscillation round the solution during the learning, so we add a supplement term to the formula (1-14).

$$\Delta w_{ji}^n = j\Delta w_{ji}^{n-1} + (1-j)\eta\delta_{pi}O_{pj} \tag{1-33}$$

where α is the momentum coefficient

This is the momentum method which is a filter, we can use it with larger learning rate and accelerate convergence.

3) It does not exist a method to determine the number of neuron in the hidden layer; A system of six neurons in the hidden layer is often a good network.

4) One hidden layer is sufficient for resolve the simple problems.

5) If there are M neurons in the input layer and N neurons in output layer, we can find a high level non - linear relationship between M input and N output with a few neurons in the hidden layer. It is a very parsimonious approximation (few weights of the synapse) then any another method (particularly polynomial).

6) Learning operation is a non- linear optimisation, we can perhaps find a local optimum. To avoid this inconvenience a Genetic Algorithms can be introduced.

7) This feed forward static neural network is not only for the pattern classification but also for the approximation of a function.

8) Another approximation is called LEVENBERG - MARQUARD, this optimisation technique is more powerful than gradient descent, but requires more memory. The two methods (Momentum, L - M) can be found in Matlab.

The neuron network is a modern statistic instrument, it is also a very parsimonious approximation method, but we don't know what it is doing. We don't know neither the causality nor the physical law. So we call this system a " black box ".

In the following, another direction of research for the bridges management is involved.

AII-1 C.A.E method (Conditional Average Estimator)*

AII-1 Introduction

Reliable treatment of natural phenomena is always based on measurements and on the description of relations between the observed test results. From the theoretical point of view, these relations can be most appropriately described in terms of abstract mathematical models representing mathematical laws. However, from the practical point of view, simulated analogue models based on electronic devices are sometimes more convenient. A generalised interpretation of phenomena arising in the field of assessment of existing concrete structures by the so called neural network like method, which can be treated by personal computer. The neural network like approach involves an empirical treatment of phenomena and intelligent systems. By simple extension of the method, which is called CAE (Conditional Average Estimator), a problem can be treated not only empirically, but also by introducing exact theoretical knowledge (e.g. Fick's law to describe the chloride - ion penetration).

AII-2 Simple presentation of CAE method

Suppose that a vector m can be divided in two parties P et Q

$$\begin{aligned} m &= \left\{ m_1, \ldots, m_M,\ m_{M+1}, \ldots, m_L \right\} \qquad (2\text{-}1) \\ &= \left\{ P,\ Q \right\} \end{aligned}$$

$$\text{where} \quad P = \left\{ m_1, \ldots, m_M \right\}$$
$$Q = \left\{ m_{M+1}, \ldots, m_L \right\}$$

P is the input vector
Q is the output vector

We can write m as following :

$$m = P \oplus Q \tag{2-2}$$

The inception hypothesis is that we don't know how to establish an equation Q in terms of P. W must built an estimator $\hat{Q}$ in terms of P. The utility method is to minimise $(Q-\hat{Q})^2$.

If we know N times m, for example, N times of the measure of the physical phenomenon. we obtain :

$$\left\{ \begin{matrix} m_{11}, \ldots, m_{1M}, \; m_{1,\, M+1}, \ldots, m_{1,\, L} \\ \vdots \qquad\qquad\qquad \vdots \\ m_{N1}, \ldots, m_{NM}, \; m_{N,\, M+1}, \ldots, m_{N,\, L} \end{matrix} \right\}$$

The vector m can be considered as a random variable, the joint probability density function is :

$$f(m)dm_1 \ldots dm_L = f(m)dPdQ = f(P \oplus Q)dPdQ = d^L \Pr(m) \tag{2-3}$$

where Pr(m) is the probability of the vector m. $dP = dm_1 \ldots dm_M$ and $dQ = dm_{M+1} \ldots dm_L$

AII-3 Estimator $\hat{Q}$

Consider estimator $\hat{Q} = \hat{q}(P) \cong Q$ (2-4)

and minimise : $D = \int \left[Q - \hat{q}(P)\right]^2 d^L \Pr(m)$ (2-5)

The preceding function can be written :

$$D = \int_Q \int_P \left[Q - \hat{q}(P)\right]^2 f(P \oplus Q)dPdQ \tag{2-6}$$

The variation's method is chosen :

$$\Delta D = -2\int_Q \int_P \left[Q - \hat{q}(P)\right] \Delta\hat{q}(p) f(P \oplus Q) dPdQ$$
$$+ \int_Q \int_P \left[Q - \hat{q}(P)\right]^2 \Delta f(P \oplus Q) dPdQ \tag{2-7}$$

The minimum is reached when $\Delta D = 0$, knowing that $\Delta f(P \oplus Q) = 0$, we have :

$$D = \int_P \Delta\hat{q}(P) dP \int_Q \left[Q - \hat{q}(P)\right] f(P \oplus Q) dQ = 0 \tag{2-8}$$

because $\Delta\hat{q}(P) \neq 0$, and we obtain :

$$\hat{q}(P) = \frac{\int_Q Qf(P \oplus Q) dQ}{\int_Q f(P \oplus Q) dQ}$$
$$= \int_Q Qf(Q \mid P) dQ \tag{2-9}$$

where $f(Q|P)$ is the conditional probability.

AII-4 Practice's form of $\hat{Q}$

In the preceding paragraph, we have found rigorously $\hat{Q}$ by the variation's method. In this paragraph, we introduce two hypotheses into $\hat{Q}$ then we can resolve practical real-world problem.

Hypothesis 1 :

The function f(m) is written in a statistical form :

$$f(m) = \frac{1}{N} \sum_{n=1}^{N} \delta(m - m_n) \tag{2-10}$$

where 1) vector's form $\delta(m) = \prod_{i=1}^{L} \delta(m_i)$ (2-11)

2) scalar's form $\delta(m_i) = \begin{cases} 1 & \text{si } m_i = 0 \\ 0 & \text{si } m_i \neq 0 \end{cases}$

With this hypothesis, we can write :

$$f(P) = \frac{1}{N}\sum_{n=1}^{N}\delta(P - P_n) \tag{2-12}$$

we know that $f(P) = \int_Q f(P \oplus Q)dQ$

where $P_n = (m_{n1}, \ldots, m_{nM})$; $n = \{1, \ldots, N\}$ et $\delta(P) = \prod_{i=1}^{M}\delta(m_i)$

The estimator can be written by the flowing formula :

$$\hat{q}(P) = \int_Q Qf(Q \mid P)dQ$$

$$\cong \sum_{j=1}^{N} Q_j \frac{\sum_{i=1}^{N}\delta(Q_j - Q_i)\delta(P - P_i)}{\sum_{i=1}^{N}\delta(P - P_i)} \tag{2-13}$$

where $\delta(Q_j - Q_i) = \delta_{ij} = \begin{cases} 1 & \text{si } i = j \\ 0 & \text{si } i \neq j \end{cases}$

We can obtain:

$$\hat{q}(P) = \sum_{j=1}^{N} Q_j \frac{\delta(P - P_i)}{\sum_{i=1}^{N}\delta(P - P_i)} \tag{2-14}$$

The preceding formula can not be useful in the practical problem, we introduce the second hypothesis :

Hypothesis 2 :

The function δ can approach by the function of normal law,

$$\delta(m) \cong \gamma(m) = \alpha e^{\frac{\|m\|^2}{2\sigma^2}} = \alpha e^{\left(-\sum_i^M m_i^2\right)/2\sigma^2} \tag{2-15}$$

where α is a constant and $2\sigma^2$ is the penal coefficient obtained by the iterative procedure in neuron network.

The estimator $\hat{q}(P)$ can be written :

$$\hat{q}_k = \sum_{i=1}^{N} q_{ik} \frac{\exp\left(-\sum_{j=1}^{M}(P_j - P_{ij})^2 \big/ 2\sigma^2\right)}{\sum_{i}^{N} \exp\left(-\sum_{j=1}^{M}(P_j - P_{ij})^2 \big/ 2\sigma^2\right)} \qquad \text{(2-16)}$$

where $\hat{q}_k$: k^{th} estimated value of the new output variable.

P_j : j^{th} value of the new input variable of investigation

P_{ij} : j^{th} value of the ancient input variable of i^{th} trial

q_{ik} : k^{th} value of the ancient output variable of i^{th} trial

AIII Algorithm of Induction of Decision Trees (I. D. 3.)

AIII-1 Introduction

Algorithm Inductive Decision Tree (I.D.3) is proposed by QUILAN in 1979. The I.D.3 is a training system of a supervised (with professors) manner in which the individuals can be divided in several classes according to certain numbers of characteristics. I.D.3 method's output shapes acquaintance in an arboraceous form, so that the IF – THEN rules can be constructed. This tree-like form is founded on the theory of transmission – information. When the causality rule can't be established, a wrong data is certainly introduced in the database. If the neuron network system is so called a black box then I.D.3 is a transparent box. It is easy to introduce the fuzzy logic and the theory of possibility into this I.D.3 method which can be adapted for different customs of bridge's maintenance (conviviality) of each country. It is also easy to class the bridges in field immediately by using minimum attributes.

AIII-2 Definition

6) $I = \{i_1, \ldots, i_i\}$ set of individuals.

7) $C = \{c_1, \ldots, c_c\}$ set of class instituted "decision" or "diagnosis".

8) $A = \{a_1, \ldots, a_a\}$ set of attributes (essential characteristic or inherent property).

9) $V_q = \{v_{q1}, \ldots, v_{qv}\}$ set of the values associated with attribute $a_q (q \in [1, a])$.

10) Definition of the SHANNON's entropy.

The entropy is the quantity of information brought by the recognition of the class of one individual between two classes c_1 and c_2 with the respective probability P_1 and P_2.

$$E = P_1 \log_2(\frac{1}{P_1}) + P_2 \log_2(\frac{1}{P_2}) \qquad (3\text{-}1)$$

7) Definitions of $n_\bullet^j$, $n_k^\bullet$ and $n_\bullet^\bullet$

For each of the attribute a_q, ($q \in [1, a]$), we can establish one table of contingent :

Attributes	V_q \ C	c_1	• • •	c_j	• • •	c_c	$n^\bullet$
	v_{q1}	n_1^1		n_1^j		n_1^c	$n_1^\bullet$
	⋮						
a_q	v_{qk}	n_k^1		n_k^j		n_k^c	$n_k^\bullet$
	⋮						
	v_{qv}	n_v^1		n_v^j		n_v^c	$n_v^\bullet$
	$n_\bullet$	$n_\bullet^1$		$n_\bullet^j$		$n_\bullet^c$	$n_\bullet^\bullet$

n_k^j : The number of individual verifying the modality of decision j, ($j \in [1, c]$), and the modality k of the value of the attribute a_q, ($q \in [1, a]$, $k \in [1, v]$).

$$n_\bullet^j = \sum_{k=1}^{v} n_k^j \qquad \text{for } j \in [1, c] \qquad (3\text{-}2)$$

$$n_k^\bullet = \sum_{j=1}^{c} n_k^j \qquad \text{for } k \in [1, v] \qquad (3\text{-}3)$$

$$n_\bullet^\bullet = \sum_{j=1}^{c} n_\bullet^j = \sum_{k=1}^{v} n_k^\bullet \qquad (3\text{-}4)$$

8) Definition of the entropy of decision $ED(c, a_q)$

The ED is defined as following :

$$ED(c, a_q) = \sum_{j=1}^{c} \left(n^j_{\bullet} \big/ n_{\bullet} \right) \log_2 \left(n_{\bullet} \big/ n^j_{\bullet} \right) \qquad (3\text{-}5)$$

$ED(c, a_q)$ measures the indetermination of the individuals of the running knot in the good class

9) Definition of conditional entropy $EC\ (c \big/ v_{qk})$

The conditional entropy c relative to the modality v_{qk} of the attribute a_q is defined :

$$EC\ (c \big/ v_{qk}) = \sum_{j=1}^{c} \left(n^j_k \big/ n^{\bullet}_k \right) \log_2 \left(n^{\bullet}_k \big/ n^j_k \right) \qquad (3\text{-}6)$$

It measures the information that brought by the acquaintance of the v_{qk} in the determination of the class of individual of the running knot.

10) Definition of the conditional mean entropy $ECM\ (c \big/ a_q)$

$$ECM(c \big/ a_q) = \sum_{k=1}^{v} \left(n^{\bullet}_k \big/ n_{\bullet} \right) \times EC(c \big/ v_{qk}) \qquad (3\text{-}7)$$

It measures the indetermination of classification, when we know the information that brought by v_{qk} distribution in difference classes.

11) Definition of information's gain $GI\ (c, a_q)$

$$GI(c, a_q) = ED(c \big/ a_q) - ECM(c \big/ a_q) \qquad (3\text{-}8)$$

AIII-3 Algorithm I.D.3

1.3 BEGIN

6) $N \subseteq E$ (N : running_knot; E : set of individuals)

7) N : = E (all individuals belong to the running_knot)

8) **IF** N is a terminal_knot (all individuals of N belong to the same class)

THEN associate the class to individuals in the terminal_knot N.

END for the terminal_knot.

IF NOT

For each a_q

Calculate $ED(c, a_q)$

Calculate $EC\left(c / v_{qk} \right)$

Calculate $ECM\left(c / a_q \right)$

Calculate $GI\,(c, a_q)$ (the maximum GI of a_q is chosen)

9) Partition running_knot into N_k knots, $k \in [1,\ v]$. (v is the number of 'value' in the attribute a_q and N_k are the children of the running_knot N)

10) For each N_k : go to 3)

1.4 END

Remarks :

3. The preceding algorithm shows that a tree can be constructed from knot_parent to knot_children. It means that the " IF THEN rules " can be easily established and a black box becomes a transparent box.

4. The improvement of I.D.3 is called neuro-fuzzy I.D.3. In this new method the membership functions of fuzzy logic and residual appurtenances are introduced for the fuzzy databases.

A-IV Example

Damage categorisation of the bridge

The damage categorisation is a function of three input parameters :

1. chloride content at the depth of reinforcing (Cl^-)

2. depth of carbonation (crbn)

3. cracks (crks)

By reason of simplification, there are only 10 samples.

N°.	Cl^- (% at cement weight)	crbn (depth in mm)	Crks (class)	Category	Group
1	0.5	5	1	1	A
2	1.2	0	3	5	C
3	0.1	1	2	2	B
4	0.1	10	1	2	B
5	0.6	3	1	2	A
6	0.0	15	3	3	B
7	0.6	0	4	4	C
8	0.2	3	4	5	C
9	0.2	5	2	2	B
10	0.1	2	1	1	A

Table A4-1: Samples of database

The problem of this example is how to divide the database of three elements (Cl^-, crbn and crks), using the CAE method, neural network and I.D.3, into 5 categories or 3 groups which are defined by the experts.

AIV-1 CAE and Neural Network results

The results of the CAE method and Neural Network method (based on Matlab program) are given in the following table:

N°	category	CAE method	Neural Network
1	1	1.44848	1.1581
2	5	4.98875	4.9267
3	2	1.84881	2.0936
4	2	1.92246	2.0249
5	2	1.56208	1.8720
6	3	2.99855	3.0061
7	4	4.13834	4.0241
8	5	4.85381	4.9371
9	2	1.86077	2.0750
10	1	1.30747	1.0205

Table A4-2: Results of CAE method and Neural Network

The simulated (possibility off line) input is also the input p for training. By reason of simplification, we didn't introduce the new input for the simulation because of the few elements in database.

For the Neural Network method, the training uses Levenberg-Marquardt method and the transfer functions are two "logsig". There is only one hidden layer with only 6 neurons (parsimonious approximation) and one neuron of output, the input matrix and the output target are normalised before training and de-normalised after simulation. The result of Neural Network depends the initiation of W (weights of the synapse) and θ (activate threshold).

AIV-2 I.D.3 results

We have only 10 points in a space of three dimensions (Cl^-, crbn and crks). It is very difficult to acquaint the characters of 5 categories. For the 3rd and the 4th category, there are only one point. The characteristic of a crowd can not be represented by only one individual. For This reason, we rearranged the database in 3 groups A, B and C, and then the " IF-THEN" rules can be built by I.D.3 method.

Before using the Algorithm I.D.3, the notion of Fuzzy logic, which are represented by the membership functions, is introduced (figure A4-1). For example the Cl^- (% at cement weight) is divided into 3 membership functions (low, middle, high). The "low" is varied from 0 to 0.6. The "middle" is varied from 0.2 to 1.0 and the "high" is varied from more than 0.6. The membership function maps each element of a variable to a membership grade between 0 and 1. We must note that the three membership functions are subjective. After calculation, the tree is showed in the figure A4-2.

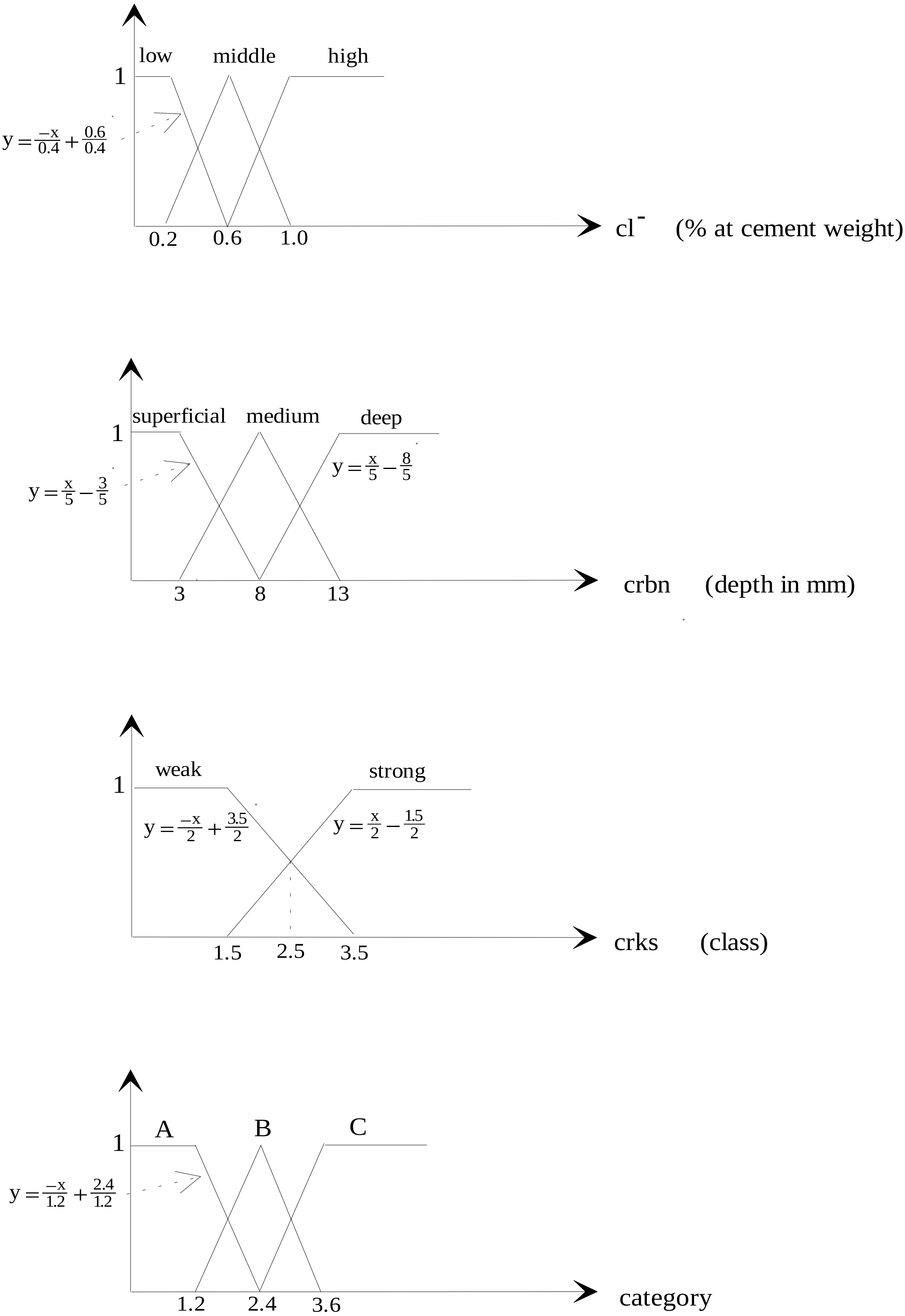

Figure A4-1: Membership functions.

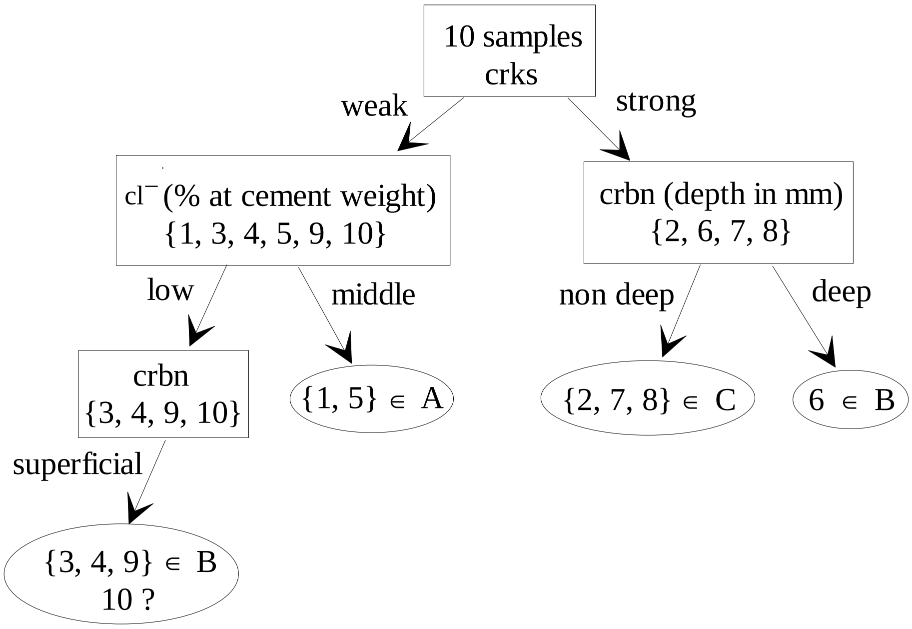

Figure A4-2: Inductive Decision Tree

We obtain four IF – THEN rules :

1. IF (crks = strong) $\wedge$ (depth = deep) then (sample $\in$ B)
2. IF (crks = strong) $\wedge$ (depth $\neq$ deep) then (sample $\in$ C)
3. IF (crks = weak) $\wedge$ (cement weight = middle) then (sample $\in$ A)
4. IF (crks = weak) $\wedge$ (cement weight = low) $\wedge$ (crbn = superficial) then (sample $\in$ B)

The sample 10 is difficult to class because the total number of samples is not enough or the database is not representative.

- The rule N°.1 can be explained as following :

  If the crks is strong and the depth of carbonisation (Cl^-) is deep then the sample is belong to group B

- Example of sample N°2 :

  The crck = 3, so in the figure 4-1, we find that it belongs to ‘ strong’ and at the same time crbn = 0, it doesn’t belong to ‘deep’ then N°.2 belongs (rule 2) to group C.

- If the number of samples is enough, we can change 3 groups to 5 categories.

Conclusion :

By comparing the results of calculation (table 4-2) of the C.A.E. and Neural Network, we find that there are not so much different between them. The feed-forward static Neural Network is a powerful methods for the classification and non linear parsimonious approximation, because it uses less parameters (synapse's weight and activate threshold) than other method with same precision. The Neural Network method combines non linear functions with adjustable or adaptable parameters. It is so called a useful, powerful parsimonious and universal method.

The Neural Network like approach involves an empirical treatment of phenomena and intelligent systems. By simple extension of the method, which is called CAE (Conditional Average Estimator), a problem can be treated not only empirically, but also by introducing exact theoretical knowledge.

For the I.D.3 method, we can find six characteristics as following :

1. Each point belonging to a particular category can be explained by IF-THEN rule which is founded on the theory of transmission – information. The number of rules can be reduced to the minimum.

2. A wrong database can be detected by I.D.3 method.

3. It can be adapted for different customs of bridge's maintenance (conviviality) of each country.

4. It is easy to introduce the fuzzy logic and the theory of possibility.

5. The classification can be done in field immediately using minimum attributes.

6. Experts' opinions or appraisements on classification even in an imprecise language can be interpreted.