A rebar corrosion decision system using machine learning

Autor(en): **Nagaraja, Srinath / Melhem, Hani G.**

Objekttyp: **Article**

Zeitschrift: **IABSE reports = Rapports AIPC = IVBH Berichte**

Band (Jahr): **72 (1995)**

PDF erstellt am: **25.09.2024**

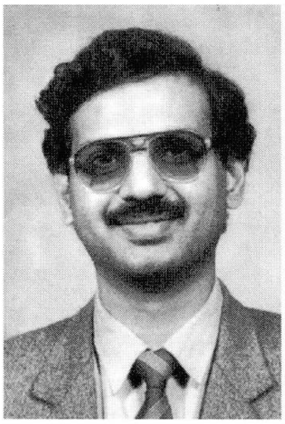
Persistenter Link: https://doi.org/10.5169/seals-54676

A Rebar Corrosion Decision System Using Machine Learning

Aide à la décision concernant la corrosion d'armatures par l'emploi d'apprentissage-machine

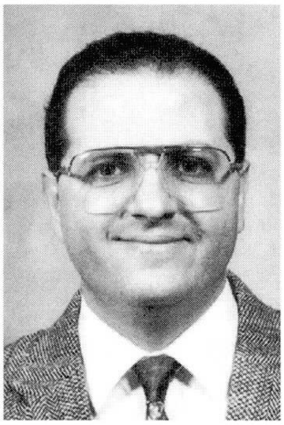
Eine Entscheidungshilfe zur Bewehrungsstahlkorrosion unter Verwendung von Maschinenlernen

Srinath NAGARAJA
Research Assist.
Kansas State University
Manhattan, KS, USA



Srinath Nagaraja, born 1966, received his BS and MS degrees from Bangalore Univ., India, in civil and structural eng. He is pursuing his PhD degree in civil eng. at Kansas State Univ. His area of concentration is expert systems application to structural and bridge engineering.

Hani G. MELHEM
Assist. Prof.
Kansas State University
Manhattan, KS, USA



Hani G. Melhem, born 1958, earned his M.S. and Ph.D. from the Univ. of Pittsburgh. He joined Kansas State Univ. in 1991 as an Assistant Professor. His areas of interest include fuzzy logic and machine learning applied to structural engineering problems.

SUMMARY

The infrastructure around the world is seriously affected by the problem of concrete rebar corrosion. This research consists of the application of a concept of Artificial Intelligence - Inductive Learning - to build a rebar corrosion expert system using machine learning programs. The resulting system could become a tool for assessing the extent of corrosion in a structure and predicting its service life. The structural examples that can be handled by the system include bridges and bridge components.

RÉSUMÉ

Dans le monde entier, les infrastructures sont mises sérieusement en danger par la corrosion des barres d'armature. Dans le cadre d'un projet de recherche, le concept de l'étude inductive par l'intelligence artificielle a été appliqué dans un système expert pour l'étude de la corrosion. Celui-ci permet d'estimer l'évolution de la corrosion dans un ouvrage d'art et de prédire la durée de vie de l'ouvrage. Il y a lieu de citer des applications possibles pour les ponts et les éléments de ponts.

ZUSAMMENFASSUNG

Weltweit sind Infrastrukturbauten durch das Problem der Bewehrungsstahlkorrosion ernstlich gefährdet. In einem Forschungsprojekt wurde das Konzept des induktiven Lernens aus der Künstlichen Intelligenz in ein Korrosions-Expertensystem übertragen. Damit können das Ausmass der Korrosion im Bauwerk bestimmt, und seine Nutzungsdauer vorhergesagt werden. Mögliche Anwendungsbeispiele sind Brücken und ihre Bauteile.

1. INDUCTIVE LEARNING APPROACH

The most difficult task in expert system development is knowledge acquisition. Recent research in artificial intelligence has resulted in several machine learning techniques that allow automatic generation of the knowledge base, the main component of an expert system. This enables merging information of both qualitative and quantitative nature using available experimental data and case studies. These techniques are supported by well formulated theories and learning-type algorithms. The Information theory is one of the most popular.

1.1 Inductive Learning and its Requirements

The successful use of induction requires having the appropriate examples with corresponding attributes, a set of classes, and a suitable induction algorithm (Hart, 1986). The examples or training set form the basis of the induction process. An incomplete or inadequate set of examples is likely to result in poor rules. The attributes are the characteristics which describe the examples and enable comparison to be made between the different examples. Some of the characteristics form the factors which influence the rules. The classes represent the decisions or classifications made by the domain experts. The inductive algorithm is the method which the computer program uses to induce rules from the training set. A summary of various inductive learning techniques and their applications has been done at Kansas State University [1].

1.2 C4.5 Machine Learning Algorithm

The most important algorithm that has been used in the C4.5 programs[2] is the process of generating an initial decision tree from a set of training cases. The evaluating criteria for the ID3 algorithm which is the forerunner of C4.5 is called *gain*, defined by Eqn. 3 below. Suppose S is set of cases, let $freq(C_i,S)$ stand for the number of cases belonging to class C_i. The notation for denoting the number of cases in a set S is given as $|S|$. To find the expected information from a message pertaining to class membership, we sum over the classes in proportion to their frequencies in S, giving

$$info(S) = -\sum_{j=1}^{K} \frac{freq(C_j,S)}{|S|} \times \log_2\left(\frac{freq(C_j,S)}{|S|}\right) \text{ bits.} \tag{1}$$

When applied to a set of training cases, $info(T)$ measures the average amount of

$$info_X(T) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} \times info(T_i) \tag{2}$$

information needed to identify the class of a case in T. (This quantity is also known as the *entropy* of the set S). Considering a similar measurement after T has been partitioned in accordance with the n outcomes of a test X, the expected information requirement can be found as the weighted sum over the subsets, as The quantity

$$gain(X) = info(T) - info_X(T) \tag{3}$$

measures the information that is gained by partition T in accordance with the test X. Although *gain criterion* gives quite good results, it has a serious deficiency-it has a strong bias in favor of tests with many outcomes. The bias inherent in the gain criterion can be rectified by a kind of normalization in which the apparent gain attributable to tests with many outcome is adjusted. The *gain ratio criterion* selects a test to maximize *gain ratio*, subjected to the constraint that the information gain must be large-at least as great as the average gain over all the tests examined.

2. CORROSION OF REBAR IN CONCRETE

Corrosion of steel in concrete structures exposed to chloride has become a major problem for bridge and structural engineers. This problem is evidenced by large scale premature failures of reinforced concrete structure in a fraction of their design life. Many of these failures have been attributed to the corrosion of the reinforcing steel and are sufficiently severe to require refurbishing or replacement of the structure [3].

When steel is exposed to an aerated alkaline solution corresponding to that found in the pores of well formulated concrete (whose pH is about 13), it corrodes to form a solid corrosion product. This product (an iron oxide) forms continuously, adherently and coherently on the metal surface and serves to stifle any further corrosion. The corrosion mechanism can be schematically represented as in Fig. 1. There is a large amount of data pertaining to corrosion of rebar in concrete. The data contains a large number of variable dependencies and cannot be processed manually.

3. DEVELOPMENT OF LEARNING SYSTEM USING CORROSION DATA

A decision system for the assessment of corrosion of steel bars in reinforced concrete structures is being developed at Kansas State University[4]. The system is composed of two main modules (Fig. 2). The first module determines the final decisions, namely, the degree of corrosion and type of remedial action. The second module predicts the serviceability life of the structure. The latter takes into consideration the important aspects of deterioration rate of rebar, the acceptable limit of deterioration, and the loss in load carrying capacity of the structure, in addition to several other important factors. The system is developed and implemented with different types of data, both numeric and symbolic in nature.

Several attributes or corrosion variables have been chosen to support the knowledge base structuring. These are broadly classified as material factors, structural factors, and environmental factors. These factors and their attributes are shown in Fig. 3. Data supporting these attributes form the basis for pattern recognition in the machine learning process. Besides the data are pre-processed using the CORRODE (Version 1.0) in order to get the decision pertaining to the servicibility life module[5].

4. CONCLUSION

Using earlier prediction models which are based on experimental results, various investigators have found it difficult to estimate the corrosion intensity in a structure. At the present time there are no reliable methods available which could use the existing prediction models. Even the most accurate test results have some degree of uncertainty. In order to remove anomalies in corrosion intensity values, machine learning techniques can be applied to understand and model the serviceability life. Using such techniques, a decision system for Rebar corrosion has been proposed and is presently under development. This type of system could help in an on-site monitoring of corrosion intensity of damaged structure.

REFERENCES

1. MELHEM H.G. and NAGARAJA S., Applications of Machine Learning in Civil Engineering. Submitted to Civil Engineering Systems, 1994.

2. QUINLAN R., C 4.5: Programs for machine learning. Morgan Kaufmann Pub., 1993.

3. TONINI, D. E. (ed.), Chloride corrosion of steel in concrete. STP-629, ASTM Publ., 1976.

4. NAGARAJA, S., A Rebar Corrosion Decision System using Machine Learning. Ph.D. Dissertation (in preparation).

5. PURVIS R., BABAEI K., CLEAR K.C AND MARKOW M.J., Life-cycle Cost Analysis for Protection and Rehabilitation of Concrete Bridges Relative to Reinforcement Corrosion. SHRP-S-377 Report, Strategic Highway Research Program, Washington D.C, 1994.

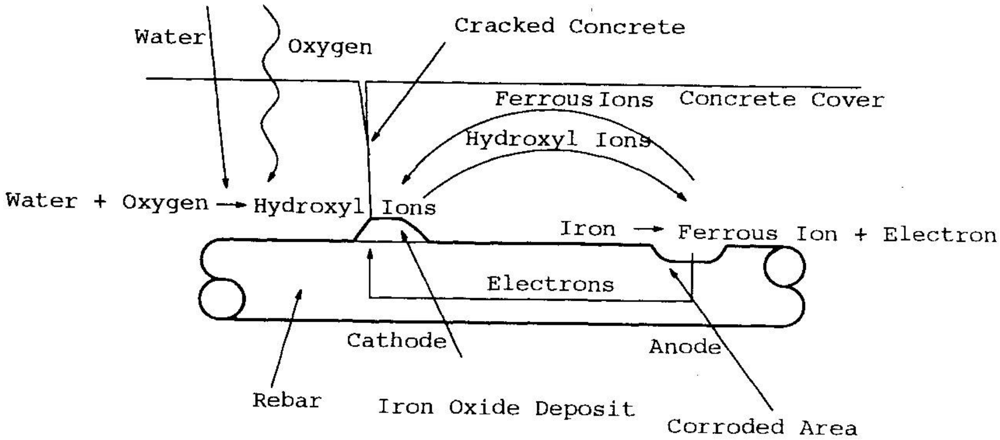


fig. 1 Corrosion Mechanism

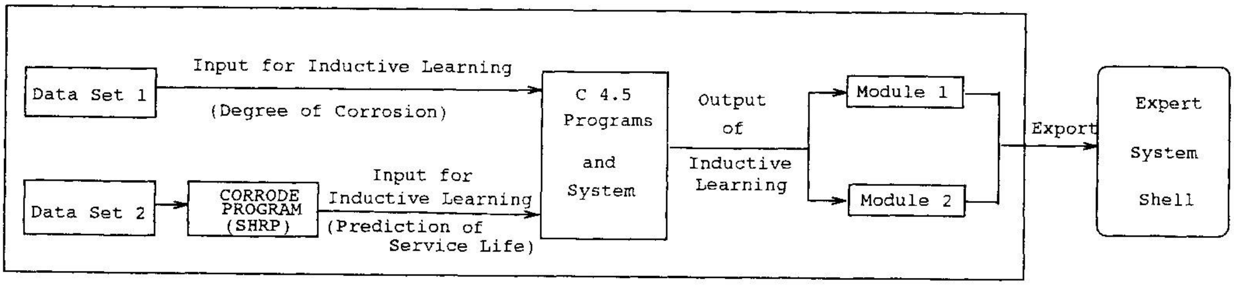


fig. 2 Architecture of System

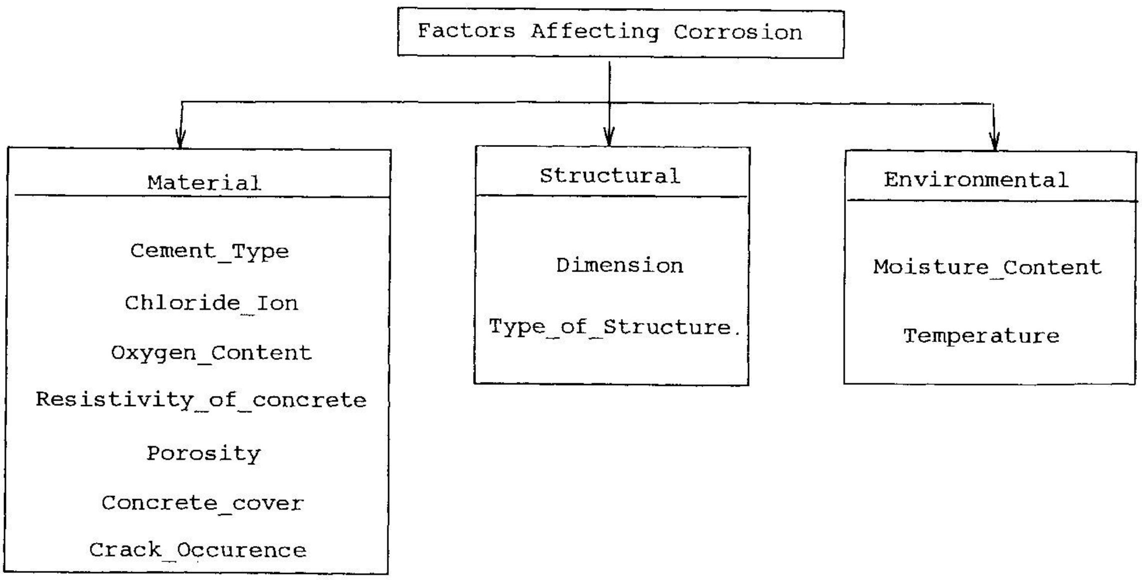


fig. 3 Factors Affecting Corrosion