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Neural networks in the advisory system for repairs of industrial concrete floors

Marcin Gajzler
Poznan University of Technology, Institute of Structural Engineering
Piotrowo 5, 60-965 Poznań, Poland
e-mail: marcin.gajzler@put.poznan.pl

An advisory system for repairs of industrial concrete floors is a supporting tool for making material and technological decisions in the sphere of problems of recurrent character. The presented advisory system has the character of a hybrid system. Various elements of tools from the artificial intelligence group have been used in it. Artificial neural networks are of particular importance for functioning of the system. They act as an inference engine. The article presents, *inter alia*, an approach in the sphere of teaching artificial neural networks on the basis of an expert's knowledge, as well as utilization of fuzzy sets for data transformation and for increasing the size of the case set. The conclusions indicate the profits resulting from utilization of artificial neural networks like speed of operation or absence of the need to possess complete knowledge.

Keywords: neural networks, advisory system, repairs, industrial floors.

1. Introduction

Artificial neural networks have had their renaissance since the turn of the 1980s. The development of the error back propagation learning algorithm was a stimulus for a renewed interest in neural networks and their application in numerous practical spheres. Today we can say without any doubt that application of artificial neural networks brings many profits. This is true in case of the problems where we do not have full knowledge and are unable to describe them, as well as in case of such problems where all the rules are known. The application of artificial neural networks in the sphere of building construction is getting more and more common as well. We can indicate, by way of examples, a wide range of problems connected with building construction, including building project engineering, where artificial neural networks are being used. To mention just a few: forecasting repair expenditures [4], assessment of technical wear [12], calculation of indirect costs of building works [10], cost management [1, 8], building project management [2, 5], or prediction of building equipment performance [9, 11].

2. Repairs of industrial floors

An industrial floor is a very important element of the building. Its technical condition is closely linked to the possibility of using the entire structure fully and in the appropriate way. In case of a considerable damage to the floor it is often necessary to exclude that area from use, which leads directly to definite losses for the owner and user of the facility. The need to make repairs will be the source of further losses. Besides, there are other negative factors of intangible character and difficult to measure, which have to be taken into account at such moments (e.g. loss of prospective contracts, reduction of reliability).

An industrial floor is influenced by many factors, some of them of extreme dimension. The type of specific influence depends on the function of a given facility. Out of numerous types of such facilities high storage warehouses have been analyzed in detail. The influences at work in such warehouses include, first of all, static loads from the supports of storage racks, loads from the movement of forklift trucks, and certain loads characteristic of each specific facility (e.g. thermal loads for cold stores/chill stores or chemical influences connected with storage of chemically aggressive materials). Instances of floor damage occur despite well recognized conditions describing loads on floors in the facilities under analysis. They occur most frequently in cases of overload (e.g. storage racks being extended or carrying too much load, the functional arrangement of the facility being changed), incidental events (e.g. heavy objects falling down, damaged packaging of chemically aggressive materials) or maintenance negligence (e.g. a small defect turns into a much more serious one with time and environmental influence). The effects of design or execution errors have been consciously ignored on the assumption that there were no errors at the stage of the investment process, and all the attention was focused on the stage of operation of the facility.

In regard to repairs of industrial floors we can say that the repair process has an algorithmized character. A visual inspection and assessment of damage is always necessary. It is accompanied by an analysis of the mechanism of damage, as well as search for causes and an attempt to eliminate or restrict them. If the latter is not possible, it is necessary to carry out repairs and reconstruction with the conditions of new influences taken into account. A lot of information concerning the damage itself and the conditions of its occurrence is acquired during those activities. That information is the basis for defining repair solution, possibly with the owner's preferences taken into account. It consists, first of all, of the chosen strategy and, second, the material and technological solution. There are many variants of material and technological solutions available on the market. Most of them are linked to specific producers who often offer support in the form of technical advisers. The presented advisory system fulfils that function to some extent as the decision making support for the repair process.

3. Advisory system

An advisory system is a tool that supports the making of decisions. Principally it is a version of an expert system specialized in the task of advising. Other examples of specialized expert systems include e.g. reviewing or monitoring systems. A hybrid advisory system for repairs of concrete industrial floors [6] is a tool supporting the technical services engaged in maintaining the facility in the sphere of making technological and material decisions at the stage of operation.

3.1. Construction of an advisory system

The construction of an advisory system (Fig. 1) is analogous to that of an expert system.

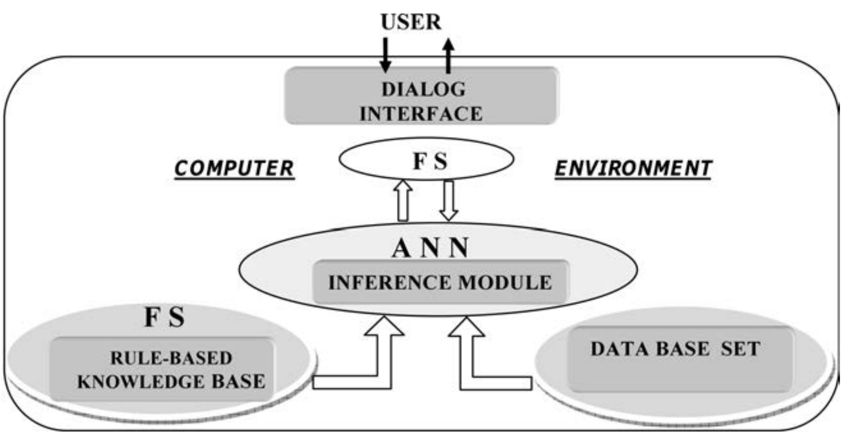

Fig. 1. Diagram of construction of an advisory system.

Its principal elements include:

- data base containing available repair materials and systems, information on recipes, process regimes, cost parameters, repair algorithms;
- knowledge base containing a collection of rules. The rules result from the conducted knowledge acquisition and derive from the mental model of the expert. The rule-based form of knowledge recording of "if ...then" type is assumed. The premises are connected with factors determining the repair process and conclusions with possibilities of utilization of the selected repair systems;
- inference engine which constitutes the central element responsible for inference within the system. The inference is actually limited to the problems of classification of material and technological solutions of the repair systems and components included in the system data base. That is the place where artificial neural networks are to be introduced as a tool capable of quick inference on the basis of incomplete knowledge;
- dialog interface as an element responsible for the dialog with the user, i.e. for transformation of the signals generated by the system and vice versa.

3.2. System assets

The assets of the system consist of data and knowledge. In an advisory system knowledge comes from the so-called branch expert. It is obtained in the course of acquisition process during knowledge acquisition sessions. Various tools and methods, e.g. interviews, questionnaires, observations etc. are used for that purpose. Automated methods [7] exist as well. In case of the system under analysis the methods used were personal interviews connected with a paper questionnaire. The knowledge acquired in that way has to be formalized in the knowledge base. The completeness is another aspect of the knowledge acquisition process. As far as we can suppose that the expert possesses large knowledge represented in the so-called mental model, its transfer is unavoidably restricted by the verbal model. The formalization of knowledge in the knowledge base is another point which restricts it. On the basis of that we can say that the knowledge included in the base represents only a part of the knowledge present in the expert's mental model.

Data are another asset of the system. Acquisition of data posed no problems due to utilization of public sources of the Internet network as well as materials from a producer of repair systems. The data are included in the data base which has been organized in regard to its content (the base of recipes, the base of repair algorithms, the base of process regimens, the base of prices).

3.3. Functioning of the advisory system

The user provides answers to questions in the course of a dialog with the system and in this way provides the system with input signals. The system-user dialog arrangement is fixed and is based on an established list of questions. The answers provided by the user have a natural form, it is allowed to use linguistic expressions of qualitative character. The information provided in that way is converted to a form acceptable for the system with the use of fuzzy sets. Due to membership functions previously defined by the expert fuzzy values are transformed into crisp ones in the process of defuzzification. As a result an input vector is created, presented further on in the inference engine. At this point artificial neural networks have been used. Those at the stage of system utilization already contain expert's knowledge, since they were subjected to the learning process on the basis of the rule-based knowledge base. After the input vector is given to the neural networks they generate the output vector which constitutes, in an indirect way, the answer given to the user. At the same time the input vector constitutes a stimulation signal for the data base from which the information connected with the solution proposed by the system is drawn.

4. Artificial neural networks

The choice of artificial neural networks for the inference engine was studied. Their principal advantages include ability to carry out inference activities in a situation of incomplete knowledge and the speed of operation. The process of formation of the artificial neural networks took place in stages. The stages were the following: preparation of data sets, selection of the type and architecture of the neural network, teaching the neural networks and full use of the neural network in the inference engine.

4.1. Preparation of the data sets

In case of the analyzed system supervised learning was used, and randomly selected rules from the knowledge base were used as the learning data. The form of the rules corresponded to "if... then..." convention, where network input signals constituted the premises while corresponding output signals were the conclusions (Table 1).

Table 1. Framework of a rule included in the knowledge base (where: A, B, ..., G – variable values; R1, ..., Rn – solutions taken into consideration).

If...	*and...*	*and...*	*and...*	*and...*	*and...*	*and...*	*Then...*
Depth of the damage	Mechanical loads	Environment	Working temperatures	Duration of influence	Application temperatures	Duration of execution	Solutions (R1, ..., Rn)
→ A	→ B	→ C	→ D	→ E	→ F	→ G	acceptance/ no acceptance

The character of the knowledge base applied in the processes of learning, validation and testing can be described as fuzzy. It included numerous variable values of qualitative character. In view of that transformation of fuzzy values into crisp ones was used in selected cases. The defined membership functions and defuzzification of values by the centre of gravity method was used there.

The size of the set of cases was another problem. There is a risk with a small size that a satisfactory quality will not be achieved with a given network architecture. There exist certain relations describing the size of the set versus the number of interneural links within the network. They suggest that a network cannot be extended if it contains a small number of cases. Negative phenomena like overfitting [3] may occur during the process of learning in the opposite situation.

The initial number of rules in the knowledge base corresponded to 164 cases, of which it was necessary to indicate the learning, validation and test samples. In view of a small number of cases the author's original method was used consisting in increasing the set of cases by using the "displacements" of the centres of gravity of the fuzzy set. The method can be compared to an introduction of artificial noise. The operation of acquiring "new" cases consisted in slight displacements of the centres of gravity of the set (Fig. 2) without causing any change in the related initial fuzzy value. The displacements in question oscillated within 50% of the range for which there was no change to the fuzzy value, to the right and left of the actual centre of gravity. The method yielded the final set containing 492 cases.

There exist several other methods of preprocessing of data before the main process beside the one described above. One of the groups of preprocessing methods [13] covers those methods that reduce dimensionality of variable spaces. The principal components analysis (PCA) method is worth mentioning in that group. The method consists in transformation of original variables into a set of new, mutually independent variables (components). The idea of the method is to combine correlated initial variables into linear combinations creating new variables, the number of which will be reduced.

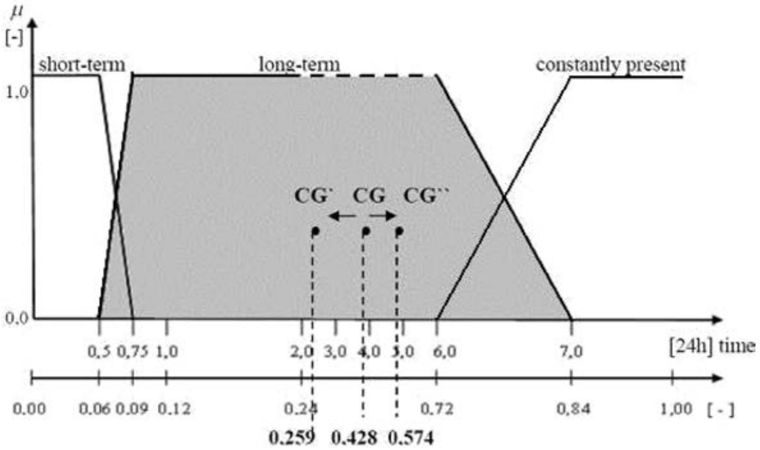

Fig. 2. Idea of displacement centers gravity.

4.2. Types, architecture and learning of networks

A class of problems connected with functioning of the advisory system is the classification describing acceptance or rejection of the discussed variants of material and technological solutions for floor repairs. In view of that, the analysis took three types of network into account: a multilayer perceptron (MLP), a network with radial basis functions (RBF) and a probabilistic neural network (PNN). Such a choice resulted from previously known applications of these networks in modelling of classification problems. The definition of architecture of artificial neural networks was basically limited to defining the number of hidden layers and the number of neurons in those layers. No preprocessing was used to reduce dimensionality of the input variables since the idea was to reflect the expert model as truly as possible. The number of neurons at the input and output of the network was determined by premises and conclusions of the knowledge base rules. In case of the hidden layers the very numbers of layers and their neurons constituted a problem. The problem mainly concerned the multilayer perceptron networks and the radial basis function networks, for which various network configurations were analysed by comparing the results (prediction statistics, network errors) and selected network configurations were assumed as a result.

The problem of size of hidden layers did not concern the probabilistic neural networks, since the number of neurons in a hidden layer was closely related to the number of data. There was another problem in connection with the probabilistic neural networks, caused by the fact that architecture of such networks reflects the entire learning set which may not be a complete and full projection of the phenomenon. It concerns, first of all, a representation consistent with reality or participation of representatives of all classes among the learning cases. If the above mentioned equilibrium does not occur, the probabilistic network may classify incorrectly. It is possible to input *a priori* the probability of occurrence of a given class in the total representation (if known) to prevent such a situation, which results in correction of the network weights.

The second method consists in introducing into the network another layer, immediately after the radial one, the so-called loss matrix which characterizes possible costs of wrong classification for a given class. In addition, there is a control coefficient, the so-called smoothing coefficient, which represents radial deviations for appropriate Gauss functions. The value of that coefficient can be established empirically, by observing the error reached by the network for a set values of smoothing coefficient.

The proper selection of learning algorithms was another problem concerning artificial neural networks. The trial and error method is one of the possibilities, however it is worthwhile to analyse beforehand the applications of various algorithms according to the class of the problem, number of cases or type and architecture of the network. The analysis utilized learning with the error back propagation algorithm for both perceptron and radial networks. The selection of learning algorithms was linked to the number of learning epochs. The number of epochs was selected individually on the basis of observations of learning errors and validation, with two criteria of stopping of the learning process being analyzed. The first concerned equalization of learning errors and validation at a set error value, the other – lack of improvement of learning errors and validation during a set number of epochs. The practical experience has shown that meeting the second criterion guaranteed better results. The entire population of cases was divided in proportions of 50 : 25 : 25% into learning, validation and test sets respectively for the purposes of the learning process and verification of the neural networks.

Another important aspect which needs to be taken into account is as follows. When analyzing the degree of complexity of the network, the process of learning and the number of learning cases we can see that it is worthwhile to use sampling methods including cross validation and bootstrap techniques in a situation of a large network and a relatively small population of learning cases. Each of these two techniques enables fuller utilization of available cases in the learning process with, simultaneously, retaining the possibility of network verification on the basis of validation and test subsets.

4.3. Multi-Layer Perceptron

The following analysis applies exclusively the Multi-Layer Perceptron (MLP) neural network, while the conclusions concerning the results obtained by means of the two remaining networks will be included in the next section.

The following configurations have been adopted for the perceptron network:

- 7-4-1,
- 7-8-1,
- 7-10-1,
- 7-15-1.

As can be seen from the above notation, the networks had 7 inputs and one output each. Instead of a network with several outlets a set of networks was used where each discussed variant of material and technological repair system had its dedicated network classifying that solution. In case of the input layer the number of neurons in that layer does not correspond to the number of inlets – it was bigger. It was the result of the method of encoding variables. In case of variables of continuous values and variables of two-state representation we have to do with a single neuron linked to that variable, while in case of multi-state representation the "one of N" encoding method was used, where "N" constitutes the number of neurons corresponding to the number of possible states of the variable.

The process of learning of MLP was carried out with the use of the classic back propagation algorithm. In selected cases the learning process was executed in two stages. The first stage included 100 learning epochs with the use of the back propagation algorithm, while the second was a continuation of learning but with the use of the conjugate gradient algorithm which is considered a 2^{nd} degree modification of the back propagation algorithm and is recommended for networks with a big number of weights. However, the learning process executed in that way brought no considerably better results than learning with the error back propagation algorithm alone, and there were cases where the final results achieved by the networks were poorer.

In addition to, the adopted criteria of stopping the network learning process the analysis of a diagram of learning errors and validation according to the number of epochs proved to be useful in practice. The learning speed coefficients were used during learning and the value of momentum was imposed. The learning coefficients were responsible for the speed and stability of learning, while the momentum was supposed to resist the error function to fall into so-called local minima.

The cross-entropy $\widehat{\mathrm{H}}$ – function (1) was adopted as the error function. It is based on a measure of information about the occurrence of a certain event, and is relatively readily used in classification problems.

$$\widehat{\mathrm{H}} = p_1 \log\left(\frac{1}{y}\right) + p_2 \log\left(\frac{1}{1-y}\right), \tag{1}$$

where p_1, p_2 – probability of occurrence of class “accepted” (1) and class “rejected” (0); y – output signal of the network corresponding to the probability modelled by the network.

Another problem concerned assessment of the quality of the network and its potential ability for correct classification. The assessment of network usefulness for execution of classification on the basis of the values of learning errors, validation and testing may be difficult and complex. The analysis of the error matrix and values of the coefficients of learning, validation and testing quality seemed a better parameter for assessment of classification ability of a network. Those parameters are directly linked to operation of a neural network and describe the results of prediction in varied ways. Obviously, the most interesting results concerned the validation and test sets, since these two sets did not participate in learning and the output signals were generated by the network just for them. The quality coefficient (2) values were calculated separately for the process of learning/validation/testing and they described the shares of correct classifications in the given sets for both states taken together.

$$Q = \frac{m_{(0,0)} + k_{(1,1)}}{n}, \tag{2}$$

where Q – quality coefficient (separately for the learning set, validation set, test set); $m_{(0,0)}$ – number of cases correctly classified as “rejected” for specific sets; $k_{(1,1)}$ – number of cases correctly classified as “accepted” for specific sets; n – total number of cases in the given sets.

A more precise picture of predictions could be seen in the error matrix which enables reading correct and faulty predictions separately for each state. Simultaneously to the above mentioned statistics the errors of learning/validation/testing were analysed, but they mainly informed about the level of learning a network has achieved. Table 2 and Fig. 3 present the selected results of neuron analysis.

Table 2. Results of the analysis for MLP 7-10-1.

Analysis no.	Set symbol	Architecture	Set number of epochs	Best network
A3 7/18	A3	7-10-1	100 (back propagation)	99 (back propagation)

Learning quality Q_L	Learning error $\widehat{\mathrm{H}}_L$	Validation quality Q_V	Validation error $\widehat{\mathrm{H}}_V$	Testing quality Q_T	Testing error $\widehat{\mathrm{H}}_T$
0.995	0.051	0.992	0.063	0.967	0.086

Error matrix:

	Learn. “0”	Learn. “1”	Valid. “0”	Valid. “1”	Test. “0”	Test. “1”
Class “0”	203	1	108	1	100	4
Class “1”	0	42	0	14	0	19

Prediction statistics:

	Learn. “0”	Learn. “1”	Valid. “0”	Valid. “1”	Test. “0”	Test. “1”
Correct [%]	100.0	97.7	100.0	93.3	100.0	82.6
Faulty [%]	0.0	2.3	0.0	6.7	0.0	17.4

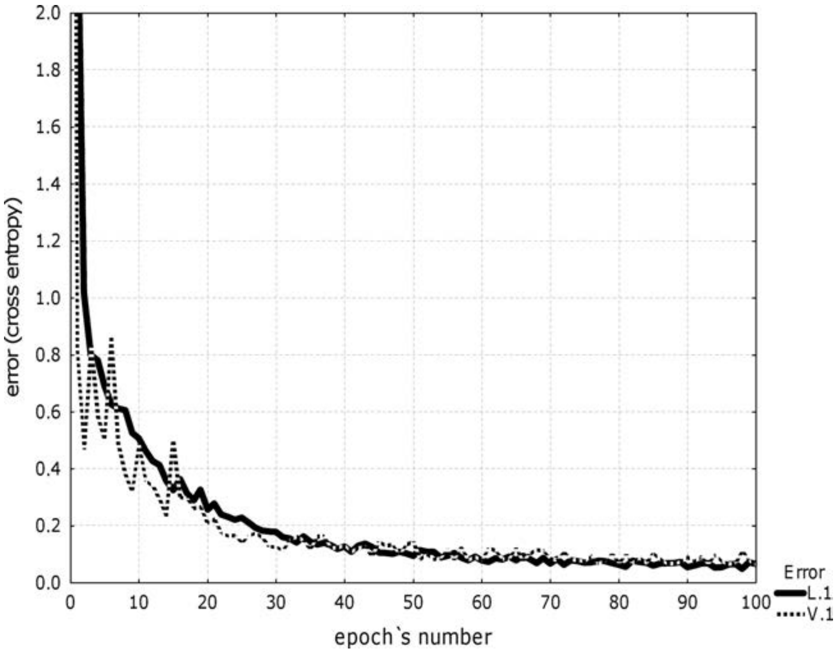

Fig. 3. Diagram of learning of MLP 7-10-1.

5. Conclusions

On the basis of the performed analysis it is possible to say that neural networks following a correctly executed learning process are very effective at classifications within an advisory system inference engine. Their principal advantages consist in the speed of operation and the possibility of transferring expert's knowledge, even incomplete, into their structure. Three types of artificial neural networks have been analysed. The analysis with the use of MLP has been described in greater detail. The results obtained for RBF network were visibly poorer. They were influenced by higher error values as compared with MLP network, and first of all the quality coefficients 15% lower on average. The results obtained for PNN were comparable with MLP results, since PNN error values and quality coefficients were close or slightly worse. The above results have been obtained for the control (smoothing) coefficient values in the range of 0.25–0.3.

The construction of complex networks of developed neural layers in case of a limited stock of cases is less effective than construction of even several simpler networks which, combined in a network unit, will operate similarly to a single complex network. Such a conclusion can be formulated after comparing the results achieved by single outlet networks, each assigned to a single material and technological variant of the repair system, with the results of a single network of several outlets in which all the variants have been taken into account.

The general conclusion concerning application of neural networks in advisory systems is that an artificial neural network after the process of learning based on expert's knowledge can successfully perform the function of expert's "virtual mind", while the advisory system itself becomes a kind of "virtual expert".

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