A DECISION SUPPORT SYSTEM FOR PAVEMENT MAINTENANCE USING ARTIFICIAL NEURAL NETWORKS TECHNOLOGY

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ABSTRACT. An important component of any Pavement Maintenance Decision Support System (PMDSS) is the condition survey and rating procedures. Data obtained from these procedures are the primary basis for determining Maintenance and Repair (M&R) actions. This paper investigates the feasibility of using Artificial Neural Network (ANN) to recommend appropriate M&R actions. In order for an ANN to diagnose an M&R action accurately, it must be trained with correct diagnosed M&R actions (training sets). Each training set consists of pavement condition and the corresponding recommended M&R action. In this study, pavement condition data used in the training sets were obtained from a comprehensive visual inspection data conducted on the Egyptian Road Network. The associated M&R actions were obtained based on consulting human expertise and M&R actions recommended by the PAVER. The results of this study reveal that ANN, trained using pavement conditions and M&R actions, has a strong potential for implementation in the PMDSS.

1. GENERAL

A typical Pavement Maintenance Management System (PMMS) would consist of several components including: (i) network coding and identification; (ii) inventory of network physical features; (iii) network condition assessment; (iv) assessment of maintenance needs; (v) producing the maintenance program based on a priority scheme; and (vi) monitoring the execution and effectiveness of the program. These components should cover three basic responsibilities of a decision maker: (i) to describe the current condition of the network; (ii) to select the most appropriate maintenance program; (iii) to monitor the execution of the maintenance program. A key element in any PMMS that has a significant value to the decision maker is the procedure through which maintenance needs (actions) are determined based on the condition of the network under consideration. This has urged researchers as well as practitioners to develop decision support systems to assist decision makers in this task. Such systems are known as the Pavement Maintenance Decision Support Systems (PMDSS)

Artificial Intelligence (AI) applications in the area of transportation engineering, in general, and in Pavement Management Systems, including PMDSS, in particular, are receiving considerable attention from transport and highway agencies [1], because of their ability to systematically formalize and use the thought process and experience of experts. The selection of M&R actions for a diversity of roadway section types, conditions, and usage levels are repeated tasks in any roadway agency that can benefit from AI applications, since these tasks are not, in most cases, made on the basis of exact engineering criteria. This is particularly true for developing countries [2], where AI applications can play an important rule in offsetting the lack of experience.

The main objective of this work is to investigate the feasibility of using the Artificial Neural Network (ANN) technology, one of the AI technologies, in PMDSS, in general, and as a decision support tool for selecting appropriate M&R actions, in particular.

Pavement condition data used in this work was selected from the results of a comprehensive visual inspection survey conducted in the Egyptian roadway [3]. The Pavement Condition Index (PCI) [4] procedure has been used in this survey to collect data on surface distresses and the corresponding severity levels and quantities (densities).

2. INTRODUCTION TO ARTIFICIAL NEURAL NETWORK (ANN)

ANN is one of the artificial intelligence algorithms that pertains to the class of machine learning. ANN mimics a human brain process of acquiring and retrieving knowledge. It models the biological neuron which consists of nodes (cells) and links (axon). It is defined as "A computing system made up of a number of simple, highly interconnected processing elements, which processes information by its dynamic state response to external input."[5]. A neural network structure consists of processing elements (nodes), links or interconnections between elements, and information processing. The processing elements and the interconnection between the processing elements represent the neural network architecture. The information processing represents the crux of the neural network. It defines how a neural network acquires and retrieves information.

2.1 ANN Architecture

Neural network's architecture includes defining the number of layers, the number of nodes in each layer, and the interconnection scheme between the nodes. Figure (1) shows a neural network architecture for a three layer network with fully connected nodes of different layers. Selection of the number of layers is controlled by the learning algorithm. Some learning algorithms require only one layer and others require a minimum of three layers. For instance, Backpropagation algorithm requires an input and an output layer and at least one middle (hidden) layer. The number of middle layers is selected based on the problem complexity (i.e. the patterns are very close to each other). The number of nodes in the output and the input layers is problem specific (i.e. governed by the task that is being analyzed). Similar to the number of hidden layers, the number of nodes in hidden layer(s) is selected based on the problem complexity.

The interconnections between nodes are controlled by the training algorithm and the nature of the problem. For instance, Backpropagation algorithm requires an interconnection between the nodes of the input and the middle layer(s) and the nodes of the middle and the output layers. The interconnection between the middle layers nodes is selected by the user (i.e. no restriction of how the middle layers are connected).

2.2 Information Processing

The information processing components are a transfer function and a learning algorithm. A transfer function defines how a processing element responds to stimulation or input data.

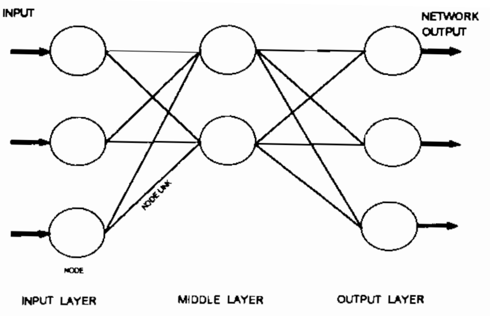


Figure 1: A Neural Network Architecture.

A learning algorithm specifies the mechanism for modifying the connection weight to achieve the desirable output. The connection weights are modified to train a raw network the training examples, retrain improperly trained network, and adapt new information (example) for a trained network. The desirable output and the input data are either autoassociative (similar) as in some unsupervised learning algorithms or hetroassociative (different) as in supervised learning algorithms

3. DEVELOPING AN ANN PROTOTYPE

Developing an ANN prototype is illustrated by tracing the life cycle of an ANN prototype from conceptual to utilization phases. The life cycle of developing an ANN prototype as shown in Figure (2) includes the following phases: neural network justification; scope identification; training sets preparation; network structure specification; network training; network validation; network implementation; and new experience adaption [6,7].

3.1 Neural Network Justification

A survey of classification tools is conducted to justify the selection of neural network for implementation. The evaluation criteria for the selected tool's required capabilities are: generalizing the classification process (i.e. not only recognizing the learned examples but also the solution space for each pattern); adapting new experiences easily; classifying numeric representation; and satisfying characteristics of the pavement condition and M&R actions. These characteristics are: the ranges for feature's values are not precisely known; the probability density function for a pattern's observations may not be known; the data represent heuristic knowledge; and observations available for each pattern may be few.

To satisfy the requirements mentioned above a number of pattern classification tools were investigated. Pattern classification is the process of dividing the feature space into regions, one region for each class. Pattern classification tools range from classical to artificial intelligent approaches. The classical approach involves one of the statistical pattern recognition methods (e.g. Bayesian approach). Artificial intelligent approaches include experts system and artificial neural network. The selection of neural network as the pattern classification tool is justified by investigating the strengths and weaknesses of the other pattern classification tools.

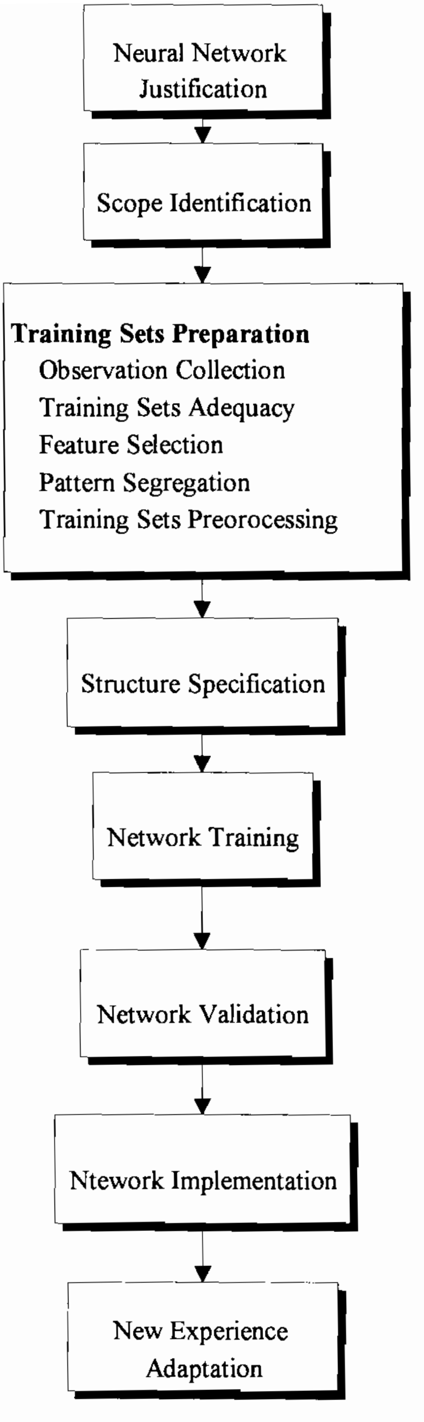


Figure 2: Developing an Artificial Neural Network Prototype

3.2 Statistical Approach

Statistical approaches have been used as a pattern classifier for problems involving a large amount of data that cannot be adequately represented mathematically or symbolically [8]. Their main advantage is the ability to provide, in addition to pattern classification, statistical data such as mean, variance, and probabilities of each pattern. Their disadvantages as pattern classifiers are the training data should be statistically sufficient to represent a pattern and the probability distribution of variables should be known before the analysis.

Neural network, on the other hand, assumes a less restrictive assumption regarding the pattern probabilities distribution. Neural network may prove to be more efficient than a statistical approach when the probability distributions are strongly non-Gaussian and are generated by nonlinear process [9]. Since neural network resembles the human decision making process of classifying patterns, it allows the use of heuristic judgement.

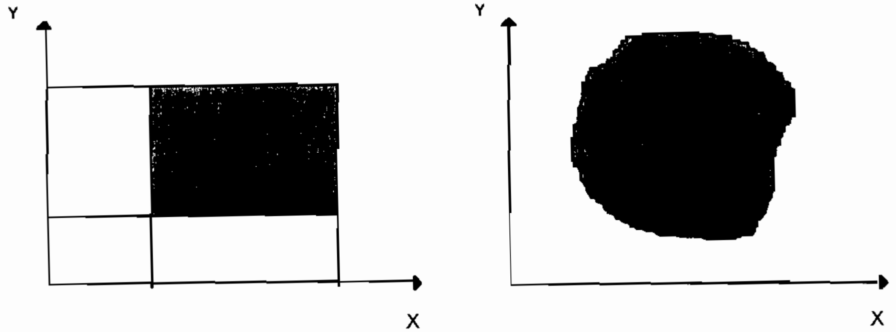
A major advantage of neural network over the statistical approach is during the implementation phase because the user does not need to possess the knowledge of neural network theory and concepts [6]. The knowledge requirements to use neural network are the ability to preprocess input data and interpret neural network output. On the other hand, the statistical approach requires the user to acquire the knowledge of statistical theory in order to prepare the input data, apply it, and analyze the output data.

3.3 Artificial Intelligence and Expert Systems

Artificial intelligence and neural network started at about the same time with the same objective: to mimic the human brain process of analyzing a problem and synthesizing a solution for it. They used different approaches to achieve their objective. The expert systems' philosophy is that every application can be symbolically represented. Therefore, the expert systems' objective is to acquire and process symbolic information in a formalized and a documented approach. The expert systems' formalization is achieved through using logical reasoning (i.e. symptoms-diagnosis procedure) to make the appropriate judgment. The documentation is achieved by using production rules (i.e. if-then rules) or one or a combination of other knowledge representation methods.

The major constraint of building an expert system is knowledge acquisition. Knowledge acquisition is conducted by a knowledge engineer who interviews and assists one or more domain experts in elicitating the relevant knowledge. Prior to the interview the knowledge engineer must have a general understanding of the problem domain in order to ask the appropriate questions and evaluate the expert responses. This process is costly and laborious.

Expert systems, however, may be more robust than neural network when representing a closed system, where the knowledge involved is well understood and can be well represented using mathematical and logical rules [8]. Figure (3) shows the application area for expert systems and neural network. An expert system is appropriate for the cases where the variable range is clearly defined as shown in Figure (3.a). With specified variables ranges, an expert system may be suitable for the decisions that require solution specialization.



A. EXPERT SYSTEM B. NEURAL NETWORK

Figure 3: Application area for expert systems and neural network

Neural network, on the other hand, in addition to alleviating the knowledge acquisition problem, is more appropriate for the cases that require solution generalization. An example of solution generalization is the shaded area, which represents a class territory, as shown in Figure (3.b). That area cannot be feasibly described. This territory, however, can be described using a number of points (examples) that are within the area. Using these examples neural network can create the solution space for the shaded area.

Selection of an appropriate M&R action for a road condition is primarily a classification task that possess the following features [10]: (1) Selection of an appropriate M&R action is based on a human expertise and knowledge (i.e. not based on algorithmic procedure or mathematical formulas); (2) Road conditions are represented numerically (e.g. densities for each distress type and severity level); (3) Ranges of road conditions to select an M&R action are not precisely defined; and (4) statistical data are not required to justify the recommended M&R action. With the previous features of specifying a suitable M&R action, ANN is appropriate for implementation in the PMDSS.

3.4 Scope Identification

The scope of ANN is to select an appropriate M&R action for pavement conditions. Pavement condition is evaluated based on the types of distresses present in the pavement and their severity levels. Distresses that affect pavements are shown in Figure (4). Severity levels of each distress type are low, medium, and high. Based on the pavement condition, an appropriate M&R action is recommended. These M&R actions are shown in Figure (4). With specifying the scope of the network, the next phase is preparing the training sets which are suitable for the specified scope.

3.5 Training Sets Preparation

The phases of preparing training sets are [6]: observations collection; training sets adequacy; features selection; patterns segregation; and training sets preprocessing.

Observations Collection. Collecting observations represents gathering raw training sets (experiences) from a source of experience that are within the scope of a network. A training

Distress Densities

Severity Level	Distress Code																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Low	d11																		
2. Med																			
3. High																			d319

Example: d11: no. of distress "1" low severity units divided by the section area
d319: no. of distress "19" high severity units divided by the section area

Suggested M&R Action												
1	2	3	4	5	6	7	8	9	10	11	12	13

Distress Codes and Names

Distress Code	Distress Name
1	Alligator Cracking
2	Bleeding
3	Block Cracking
4	Bumps & Sags
5	Corrugation
6	Depression
7	Edge Cracking
8	Joint Reflective Cracking
9	Lane / Shoulder drop off
10	Longitudinal Cracking
11	Patching & Utility Cuts
12	Polished Aggregate
13	Potholes
14	Railroad Crossing
15	Rutting
16	Shoving
17	Slippage Cracking
18	Swelling
19	Weathering & Raveling

M&R Codes and Names

M&R Code	M&R Name
1	Do nothing
2	Crack seal
3	Skin patch
4	Partial depth patch
5	Full depth patch
6	Pothole filling
7	Apply heat & role sand
8	Apply surface seal emulsion
9	Apply rejuvenation
10	Apply aggregate seal coat
11	Thin overlay
12	Thick overlay
13	Strengthening thin overlay

Figure 4: Data Summary Form

set consists of a number of features and their values as well as the correct classification for it. Raw training sets represent the pavement condition which include the density and the severity of each distress type available in the sample unit and the appropriate M&R actions.

Raw training sets represent pavement condition data that are selected from a comprehensive visual inspection of the Egyptian road network [3]. The associated M&R action was determined through consulting human expertise (district mangers and engineers) and through the use of the intervention logic rules of the PAVER (a pavement management system developed by the U.S. Army Corps of Engineering).

Training Sets Adequacy. Training sets adequacy includes providing sufficient and indicative data to represent the patterns appropriately. A number of training sets should be provided for each pattern because ANN constructs for each pattern a region in the solution space based on the training sets that pertained to that pattern. The number of training sets used were 55 sets. Providing indicative training sets for each pattern allows the network to appropriately set the pattern solution space boundaries in order to reduce the misclassification rate (i.e. increase reliability). To satisfy the indicative condition, each training set provides new information (i.e. no redundancy).

Feature Selection. The feature selection process specifies key features that are sufficient to represent a pattern. For the PMDSS all of the nineteen distress types and their three severity levels are required to select M&R actions. Consequently, all of the distresses are considered to be as key features.

Patterns Segregation. Patterns should be easily separable. If patterns are very close to each other, the training time will be very long. Furthermore, the network may not be able to distinguish between patterns. Neural network, however, can be used even if the patterns are close to each other through using a functional link node. The objective of a functional link node is to increase the dimension space of the input data. Increasing the dimension space magnifies the difference between patterns, consequently, the network can learn these patterns faster. In this research the ANN learned the training examples without adding a functional link node.

Training Sets Preprocessing. Preprocessing input data involves presenting training sets in a way that is acceptable to the ANN. Preprocessing represents normalizing the features' values. The normalization process can be accomplished through using vector calculation, dividing by a constant, dividing by the maximum value that a feature could have within the scope of the network, or using any function that satisfies the transfer function range. The functions of the normalization process are [7]: to reduce the variability of the ranges of features value; to group training sets that pertain to each class close to each other; to disperse the training sets that pertain to other classes; and to reduce the possibility of early network saturation. Normalization process may be necessary if there is a wide difference between the ranges of feature values. In a case that has been investigated during training the network, the range for potholes is between 0.0 and 0.04 and the range for block cracking is between 0.0 to 100. The network could not learn until these features were normalized.

Network saturation refers to having large connection weights. With large connection weights the network cannot easily enhance its performance because the weight modification will be very small. Therefore, the input data should be normalized to prevent this problem.

The normalization procedure used is to divide densities of each distress type by the maximum possible density in order to have all the distress's densities within the range of 0.0 to 1.0. After preparing the training sets, the next phase of developing an ANN prototype is specifying the network structure.

3.6 Network Structure Specification.

Neural network structure represents the learning algorithm and the neural network architecture. The learning algorithm is the heart of neural network because it specifies how to modify the connection weight in order to improve the performance of the ANN Backpropagation algorithm was selected because it is the leading and the most widely used learning algorithm [11]. The architecture of the neural network defines the preceded and succeeded nodes for each node in the network. Network architecture includes identifying the number of layers, the number of nodes in each layer, and the connection scheme between the nodes of different layers. Input and output layers and at least one hidden layer are the minimum number of layers required by the Backpropagation training algorithm [6].

The number of hidden layers should be selected to satisfy three concepts. The first concept is that as the number of hidden layers increases, the network speed of learning increases [12]. If the number of hidden nodes is insufficient, the network may not learn or learn after a long time (i.e. convergence become difficult to achieve). The second concept is that as the number of hidden layers and nodes increases, the network behavior tends to remember the specific patterns [13] rather than generalizing the learning process. Remembering particular patterns contradicts with the principle of neural network that is generalizing the learning process. The third concept is that as the number of hidden nodes increases the connection weight become more difficult to estimate from the training sets [14]. To satisfy these view points a sensitivity analysis should be conducted for the number of hidden layers and nodes in each hidden layer. The objective of this analysis is to select the minimum number of hidden layers and nodes in each hidden layer that are sufficient to train the network. The output of the sensitivity analysis revealed that one hidden layer that consists of forty nodes is sufficient to train the network.

The second aspect of network architecture is the number of nodes in each layer. The input layer consists of fifty seven nodes. These nodes represent the nineteen distresses and the three severity levels for each distress type (i.e. 19 x 3). The number of nodes in the hidden layer is forty as mentioned before. The number of output nodes are thirteen. The number of nodes in the output layer represents the number of patterns that the ANN can recognize. Each pattern represents an M&R action.

The third aspect of neural network architecture is the connection weights scheme or the links between nodes of different layers. The connection scheme used in the neural network is to fully connect the nodes of different layers. Full connection represents that each node is connected with all nodes of the succeeding layer.

3.7 Network Training

The network training represents acquiring the knowledge of classifying patterns. The training process involves propagating training sets through the network and the network output is calculated. Then, the output error is calculated which is the difference between the network output and the desired output. If the accuracy level is not achieved, the network modifies the connection weights. Then, training sets are presented again to the network and the network output is calculated. The cycle of presenting training sets, calculating network output, computing error value, modifying connections weights, and introducing training sets again is continued until the network achieves the desired accuracy level. If the error value is within the accuracy limit, the network is considered to be trained and it is ready for the validation phase.

3.8 Network Validation

The validation process is conducted to verify the network reliability. Validating a network is achieved by presenting testing sets to the network. These sets should be new sets that the network have never been exposed to these sets before. Network output using these sets is compared with the desired output to calculate the accuracy rate (i.e. reliability). If the accuracy rate is low, then the network is not properly trained and other training sets should be generated to retrain the network. Otherwise, the network is considered to be reliable and ready for implementation. The number of testing sets used is thirty sets. The developed network achieved 66% accuracy rate.

3.9 Network Implementation

After achieving the reliability level, the neural network is ready for implementation. One of the advantages of the neural network is that it does not require a sophisticated knowledge from the end user to implement it. It requires the user to know the normalization factors for the input features and the output data interpretation. The output data are the activation level of the output layer nodes. Since each output node represents a specific pattern, the recommended pattern depends upon the associated node activation level. Using expert system terminology, the activation level represents a confidence factor for each pattern. The node that has the highest activation level is the recommended node. The associate pattern for this node is then identified by the user. The activation level for each node is a value within the transfer function limits (e.g. 0 to 1 for sigmoid function).

3.10 New Experience Adaption

Network adaption is one of the important characteristics of the neural network. The adaption phase represents updating the neural network knowledge with new experiences. These experiences are prepared following the process discussed before. Then, these data are appended to the training sets file that is used to train the network. The network is then retrained following the same training procedure.

4. CONCLUSIONS

The developed network achieved the requirement of the first phase for this research that is the feasibility of using ANN to recommend appropriate M&R actions based on pavement condition. With specifying the structure of the network and the training data preparation method that were mentioned before, the network achieved a good reliability level to conduct the second phase of this research. The second phase will be to enhance the network reliability by reducing the input features (distress types) and investigating the gray areas between the M&R actions as will as including other features that are importan for the planner.

5. ACKNOWLEDGMENT

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