CONDITION ASSESSMENT OF PRE-STRESSED CONCRETE CYLINDER PIPELINE USING ARTIFICIAL NEURAL NETWORKS

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الملخص

تتعرض الأنابيب الخرسانية سابقة الاجهاد (PCCP) إلى بعض المشاكل. التي توثر على تقييم حالة وأداء خطوط الانابيب بواسطة الفحص المباشر باستخدام تقنيات متمثلة في الرنين المغناطيسي والرصد الصوتي أو الرادار GPR. ومن الطرق العلمية شائعة الاستخدام فحص مقاطع محددة من خطوط الانابيب في أوقات معينة، نتيجة التكلفة العالية الناتجة من عملية الفحص المباشر وعدم القدرة على تطبيق تقنيات تحت ظروف التشغيل التي تسود داخل خطوط الانابيب. وقد تعطي اعمال الفحص المباشر صورة غير كاملة عن حالة خطوط الانابيب. ويمكن تحسين هذا الوضع عن طريق استخدام نماذج ذكية قادرة على التنبؤ بالوضع الحالي وأداء نظام خطوط الانابيب بناءً على نتائج الفحوصات السابقة لهذه الانابيب. لقد تم في هذه الدراسة تطوير نماذج للتنبؤ بانقطاع الاسلاك في أنابيب خرسانية سابقة الاجهاد (PCCP) باستخدام تقنيات الشبكات العصبية الاصطناعية (ANN)، حيث تم تطبيق هذه النماذج على البيانات الناتجة من عمليات الفحص بالرصد الصوتي على أنابيب خرسانية سابقة الاجهاد في مشروع النهر الصناعي. وقد أظهرت نماذج الشبكات العصبية توافق جيد جداً مع نماذج التدريب واعطت نتائج جيدة في التنبؤ. وتستخدم حالياً هذه النماذج بشكل روتيني في التنبؤ بانقطاعات اسلاك الانابيب الخرسانية سابقة الاجهاد بمشروع النهر الصناعي.

ABSTRACT

Many owners of Pre-stressed Concrete Cylinder Pipe (PCCP) around the world experience regular failures in their pipelines. The condition and performance of any water pipeline can be assessed by direct inspection using techniques such as electromagnetic resonance, acoustic monitoring, or GPR radar. It is common practice to inspect only a few sections of a pipeline at any point in time. This is largely due to the very high costs associated with direct inspection and the inability to apply direct inspection techniques under the operating conditions that prevail inside the pipeline. Thus, direct inspection activities can only provide a very incomplete picture of the state of the water mains. The situation can be improved with the use of intelligent models capable of predicting the current condition and performance of the pipeline system based on observations of historical conditions and inspection of the results. We have developed such models for PCCP wire break predictions using Artificial Neural Network (ANN) techniques. The models are applied to real-world acoustic monitoring data collected from the Man Made River Project (MRP) in Libya. The ANN models are in good agreement with the training patterns and show good prediction performance. The developed models are now routinely used for the prediction of PCCP wire breaks by MRP.

Keywords: Water Mains; Pre-stressed Concrete Pipes; Wire Breaks; Neural Network; Acoustic Monitoring.

INTRODUCTION

Many water authorities and agencies around the world use Pre-stressed Concrete Cylinder Pipes (PCCPs) as transmission and distribution systems. As these systems degrade over time, the evaluation of their structural integrity and performance becomes a major concern for owners and operators. Corrosion-induced failure in the pre-stressing wires of PCCP can result in ruptures with consequent interruption in service, damage to property and repair costs. Such ruptures tend to occur suddenly without prior anticipation by the operator.

According to Makar and Kleiner [1], there are two possible approaches to assess the condition of water pipelines. The first approach, *indirect indicators and statistical methods*, involves the collection of data related to pipe damage. This data could be used to develop statistical indicators or intelligent models to assess the condition of the pipes. The second approach, *direct inspection and monitoring techniques*, involves the inspection of the pipeline using non-destructive evaluating techniques (such as remote field eddy current/transformer coupling, acoustic monitoring or GPR radar), which detect problems (defects) in the pipes. In general, the second approach is severely hampered by limited access to the buried pipes and the high cost associated with conducting non-destructive inspections, which prevents the constant monitoring of the pipes. The first approach would require model development.

Artificial Neural Networks (ANNs) present a promising direction for the development of predictive models to assess the pipe condition because of their learning ability and the property of generalization. A number of successful developments of ANNs for condition assessment of different types of buried pipes have been presented lately. Systems with PCCPs have not been addressed to date.

Najafi and Kulandaivel [2] presented an ANN model for predicting the sewer pipes condition based on historical data. A back-propagation neural network algorithm was used for training and testing. Seven input variables were used for the neural network modeling, namely length of pipe segments, diameter of pipe segments, type of pipe material, age of pipe, depth of cover, slope of pipe segments and type of sewer. Al-Barqawi and Zayed [3] applied the ANN approach to develop a model for assessment and prediction of water mains condition rating. Their research covered three types of pipes, namely asbestos, cast iron and ductile iron pipes. The input variables included pipe type, size, age, breakage rate, Hazen-Williams factor, excavation depth, soil type and top road surface. More recently, a neural network model for prediction of water cast iron pipeline failure has been reported by Achim, Ghotb and McManus [4]. The developed model included six input variables: pipe diameter, year of construction, pipe age, length and the pair of geographical coordinates. The model was developed to predict the number of failures that would occur in a pipeline per kilometer and year.

Geem et al [5] present a water pipe condition assessment model to predict the overall pipe condition index using ANNs. The model has been applied to real-world system in South Korea. A back-propagation neural network algorithm has been used for training and testing. The model incorporates eleven inputs: pipe material, pipe diameter, pressure head, inner coating, outer coating, and electric recharge, bedding condition, pipe age, trench depth, soil condition and number of road lanes.

This paper presents the first development of ANN models for the prediction of PCCP conditions. The models are implemented on the basis of a large real-world system in Libya, the Man-Made River Project (MRP). The Man-Made River Authority (MRA), the authority dedicated for the implementation and operation of the MRP, experienced a series of five pipe ruptures between August 1999 and April 2001. The reason of these ruptures was the corrosion-induced failure of the pre-stressing wires of PCCP. At the beginning of the problem, MRA developed a simplified pipe classification model known as Pipe Criticality Index (PCI). This index assisted in ranking the distressed pipes according to their criticality, which helped in prioritizing inspection and monitoring as well as the establishment of repair and replacement plans for affected sections of pipelines. At the same time, MRA recognized the need for a long-term management tool that would facilitate more comprehensive repairing and maintenance decisions. Moreover, enable taking the appropriate preventive measures through continuous monitoring and estimation of the remaining service life of each pipe. Thus incorporating structural, chemical and statistical models based on pipe databases as well as all data collected from non-destructive inspections. The ANN models presented in this work have been developed to address these needs. They provide managers and operators of PCCP water mains with a means to determine cause and time deterioration of their PCCP is occurring so as to enable to better decision-making about monitoring, inspection and rehabilitation of the pipeline networks.

APPLICATION BACKGROUND

The MRP is a major water supply project in the State of Libya. It was constructed to extract and convey high quality ground water from deep aquifers in the Sahara Desert to the northern coastal strip where over 90% of the population lives. To date, three phases (I, II and III) of the project have been completed and are under operation. These consist of 463,440 (3,847 km) PCC pipes of mainly 4.0 meter diameter that transport four million cubic meters of water per day from 674 production wells at Sarir, Tazerbo, East Jabal Hasouna and North East Jabal Hasouna to end reservoirs at coastal strip. The layout of these phases as well as the future phases is shown in Figure (1) [6, 7].

Figure 1: Layout of MRP phases (MRA, 2009)

MRA experienced a series of five ruptures in 4.0 m diameter pipes of the Phase I system. The first pipe ruptured was on 19 August 1999 while the second rupture was on 04 September 1999. Three more ruptures occurred between January 2000 and April 2001. Locations of these ruptures on the pipelines are shown in Figure (2).

On-site investigations and studies carried out by MRA concluded that the ruptures were caused by the corrosion-induced failure of the pre-stressing wires. All these ruptures resulted in an emergency (unplanned) shutdown, which is not acceptable to MRA as the project supplies water to the most of urban communities along the MRP pipeline route.

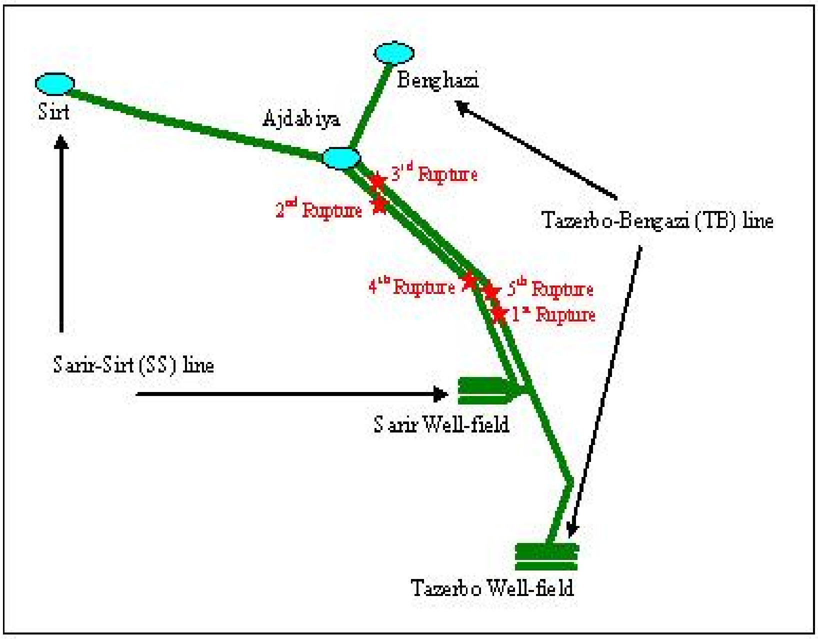

Figure 2: Locations of pipe ruptures on Phase I pipelines

To minimize the risk of occurrence of more rupture events and maintain the uninterrupted flow of water, MRA adopted a full-scale rehabilitation program aimed at identifying and treating all affected pipes. This plan involved conducting an assessment program for pipeline condition based on Non-Destructive Testing (NDT), and installing a Cathodic Protection (CP) system on the entire Phase I system. A simplified pipe classification model was established and used to classify the distressed pipes according to their criticality. The rehabilitation program has enabled MRA to conduct a successful selective and preventive maintenance to extend the service life of its enormous and complex pipeline network. Since April 2000, the date of using NDT techniques in MRP, MRA has inspected a total of approximately 1655 km of Phase I pipes using both Remote Field Eddy Current/Transformer Coupling (RFEC/TC) and P-Wave. Some sections of pipelines have been inspected three times over a period of 6-years. In total, 6960 pipes were found to be distressed. All those distressed pipes were uncoated (white) pipes. Phase I pipelines consist of 60% (1176 km) uncoated pipes and 40% (750 km) coated (black) pipes. Also, MRA had installed an acoustic monitoring system to monitor sections of their pipelines. It has monitored 173 sites spanning 316.3 kilometers of white pipe sections. Some of these sites have been monitored twice. A very large amount of data has been collected showing wire breaks as they occur in real-time. This wealth of data can be exploited with the use of ANNs in order to predict future PCCP failures.

DATA COLLECTION AND SELECTION OF ANN MODEL INPUTS

Results of acoustic monitoring such as number, location, date, time and type of the pre-stressing wire breaks are recorded, as they occurred, and saved into the acoustic monitoring database. A total of 9035 records of data containing pipe ID, number of recorded wire breaks, and time between first and last wire break were prepared and linked with both Pipe As-Built and Pipe History databases in order to extract the most important design, physical and environmental available data that have the major effect on the deterioration process of PCCP.

Table 1: Input variables included in the ANN model

No.	Type of variable	Name of variable	Description of variable	Range of variable
1	Physical	Monitoring period	The monitoring time between first and last wire break for a pipe	30 to 900 days
2		Pipe age	The time period between pipe installation (laying) and the occurrence of first wire break	4349 to 6640 days
3	Envier.	Soil resistivity	Average soil resistivity on 4m depth	continuous values (in ohm-cm)
4	Design	Pressure rate	Pipe design pressure	6, 8, 10, 12, 14 and 16 (bars)
5		Soil density	Pipe design soil density	1900, 2050 and 2100 (kg/cm^3)
6		Soil cover	Design height of soil cover on the pipe	2.8, 3.0, 4.0 and 5.0 (m)
7		Wire wrap	Type of pre-stressing wire wrap: single or double	1=Single or 2=Double
8		Wire diameter	Diameter of pre-stressing wire	4.88, 6.35 and 7.25 (mm)
9		Wire pitch	Distance between two adjacent pre-stressing wires in the same wrap	9.82 to 22.33 (mm)

Nine variables (factors) were identified and selected as inputs to the proposed ANN model. Description of these variables is presented in Table (1), and an illustration of the designed ANN structure with input and output variables is shown in Figure (3).

Previous MRA studies concluded that the rate of wire breaks recorded by acoustic monitoring pre and post installation of CP system for both Standard and Special pipe type is different. This was investigated through the on-site inspections and excavations conducted on the pipelines [8]. Based on that, the collected set of data has been divided into four groups in order to increase the performance of the neural networks and achieve high accuracy of predicted outputs.

- Group 1: *SP-Before CP* contains Special Pipes (SP) that recorded wire breaks prior to the installation of the CP system.
- Group 2: *SP-After CP* contains Special Pipes (SP) that recorded wire breaks after the installation of the CP system.
- Group 3: *ST-Before CP* contains Standard Pipes (ST) that recorded wire breaks prior to the installation of the CP system.
- Group 4: *ST-AfterCP* contains Standard Pipes (ST) that recorded wire breaks after the installation of the CP system.

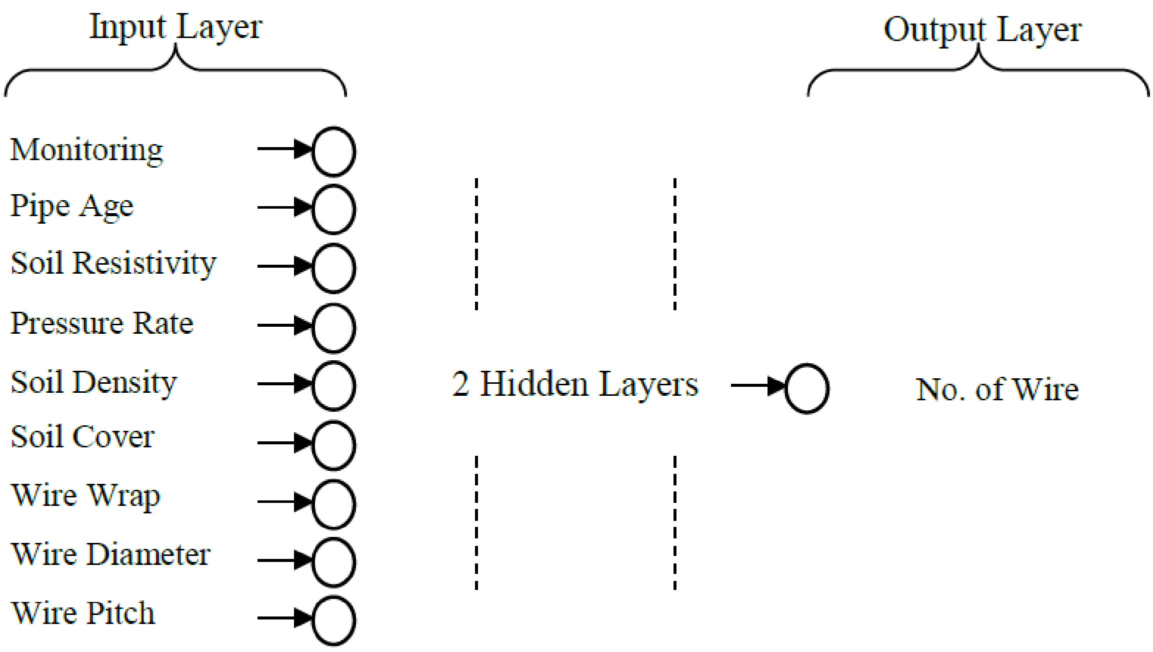

Figure 3: Wire breaks prediction ANN model

TRAINING OF ANN MODEL

Once the ANN has been designed, it has to be trained in order to produce the expected output values. This training operation is accomplished by selecting a proper training algorithm for the problem to be solved. Several training algorithms have been developed for ANNs. Among various existing training algorithms, Back-Propagation algorithm was selected in this research work. It is commonly used algorithm, and has been proven to be successful in practical applications, despite its disadvantages of being time-consuming and complex. [9-11].

To successfully apply ANN in prediction of PCCP wire breaks many input variables have to be converted into a suitable format for presentation to the neural networks. The data representations of the neural network inputs are categorized into two groups. The first group has a continuous-valued data type and will be properly scaled, and the second group has an enumerated data type and will be properly encoded and decoded.

The dataset of 9035 patterns (each pattern formed by input and output vectors) has been randomly split into 90% of the data for training and 10% of the data for testing.

Number of patterns allocated to the training and testing for each group are shown in Table (2).

Table 2: Allocation of training and testing data patterns

Group of Data	Training (90%)	Testing (10%)	Total
SP-Before CP	481	53	534
SP-After CP	831	92	923
ST-Before CP	1931	214	2145
ST-After CP	4890	543	5433
Total	8133	902	9035

Several training experiments with various combinations of training parameters have been carried out to identify the optimal network structure and configuration that produces minimum errors during the training phase. Due to the limited time available for conducting this research, some of parameters such as number of hidden layers and number of hidden neurons in each hidden layer were predetermined as 2 and 15 respectively. These values are considered adequate for the complexity of the network in this work but should be fine-tuned in the future. Other training parameters such as learning rate and momentum values have been changed (increased and decreased) during the training process in order to increase the complexity of the network structure. We consider that the network has learned the representative examples well enough when the error has reached a value lower than a predetermined limit, or the number of training cycles has reached a value equal to a predetermined limit. Table (3) presents the training error and iterations limit values for each group.

Table 3: Errors and iterations training limit values

Group of Data	Error limit	Iterations limit
SP-Before CP	1	30000
SP-After CP	1	30000
ST-Before CP	10	20000
ST-After CP	10	75000

TESTING OF ANN MODEL

At the end of the training phase, the experiment that produced lower error value in each group has been selected to verify its performance and generalization capability. This is done by carrying out a validation test, which includes exposing the network to a new subset of inputs not previously seen by the network. The predicted outputs were then compared with the actual outputs. If the validation test shows acceptable results then the neural network is validated, otherwise, the network has to be retrained by adding to the training sets the situations of the test sample that generated unacceptable results. The development procedure of the proposed ANN model is illustrated in Figure (4).

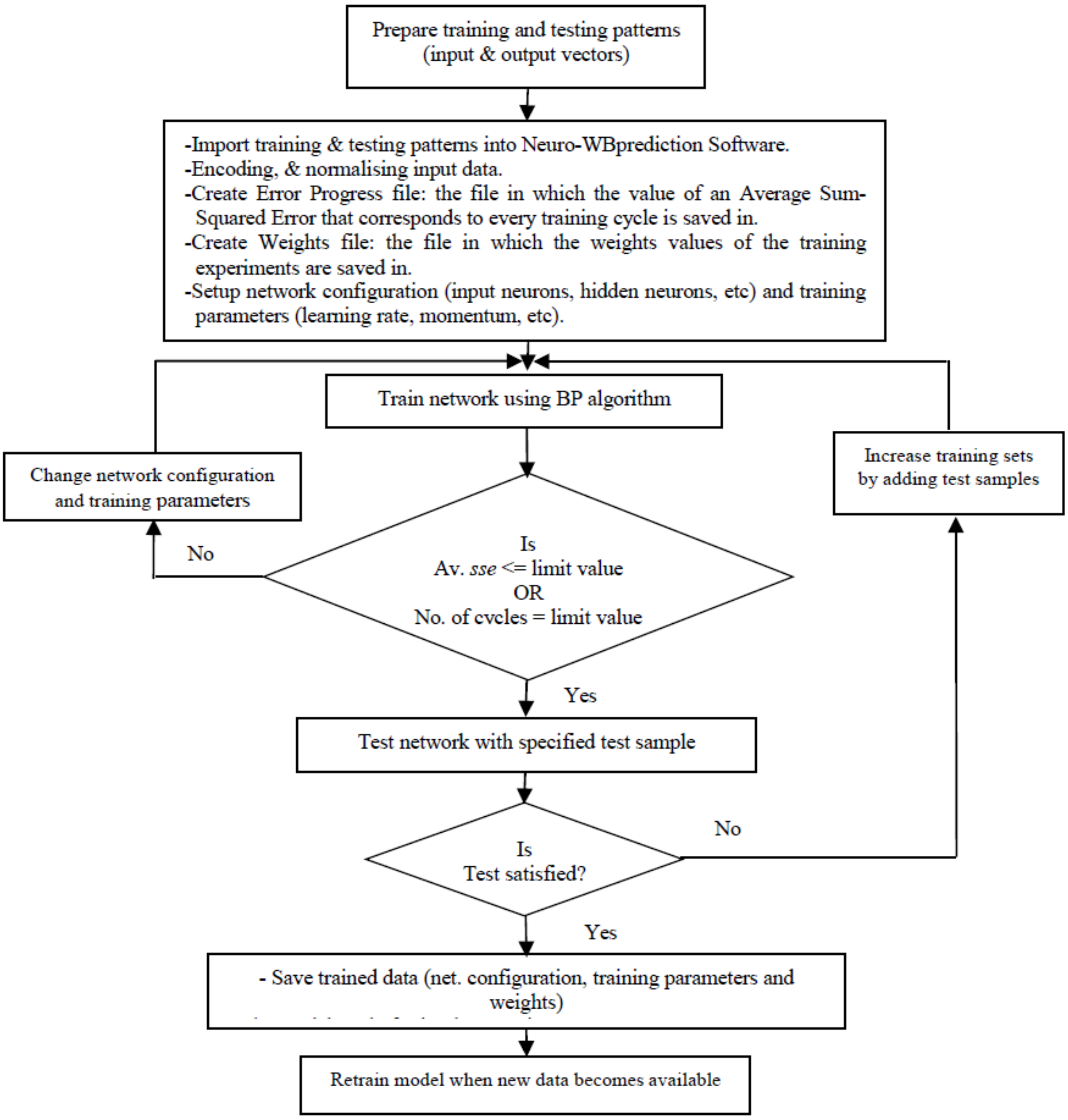

Figure 4: ANN model development procedure

RESULTS AND DISCUSSION

With implementing the training and testing procedure adopted in this research work, twenty training experiments (five for each group) have been carried out as shown in Table (4). The experiments marked with asterisk (nos. 2, 6, 11 and 16) have presented the best network structures.

Table 4: Training experiments data of ANNs implemented in the research

Exp. No.	Network Name	Inputs	Outputs	Hidden Layers	Hidden Neurons	Learning rate (η)	Momentum (α)	Training Pattern	epoch	Average sse
1	SP-Before CP	11	1	2	15	0.1	0.9	481	300000	9.111
2 *		**11**	**1**	**2**	**15**	**0.3**	**0.7**	**481**	**300000**	**5.121**
3		11	1	2	15	0.5	0.5	481	300000	7.687
4		11	1	2	15	0.7	0.3	481	300000	17.396
5		11	1	2	15	0.9	0.1	481	300000	13.398
6 *	SP-After CP	**11**	**1**	**2**	**15**	**0.1**	**0.9**	**831**	**300000**	**2.394**
7		11	1	2	15	0.3	0.7	831	300000	3.518
8		11	1	2	15	0.5	0.5	831	300000	45.543
9		11	1	2	15	0.7	0.3	831	300000	2.857
10		11	1	2	15	0.9	0.1	831	300000	3.244
11 *	ST-Before CP	**11**	**1**	**2**	**15**	**0.1**	**0.9**	**1931**	**200000**	**108.21**
12		11	1	2	15	0.3	0.7	1931	200000	110.58
13		11	1	2	15	0.5	0.5	1931	200000	115.12
14		11	1	2	15	0.7	0.3	1931	200000	109.02
15		11	1	2	15	0.9	0.1	1931	200000	110.16
16 *	ST-After CP	**11**	**1**	**2**	**15**	**0.1**	**0.9**	**4890**	**75000**	**44.377**
17		11	1	2	15	0.3	0.7	4890	75000	46.389
18		11	1	2	15	0.5	0.5	4890	75000	49.651
19		11	1	2	15	0.7	0.3	4890	75000	52.440
20		11	1	2	15	0.9	0.1	4890	75000	51.093

The graphs shown in Figures (5-8) represent the training average *sse* on the y-axis against the number of epochs elapsed on the x-axis for the best networks (experiments). Epochs represent a complete pass through the network of the entire set of training patterns. The graphs generally illustrate downward movement of the error rate as learning progressed, indicating that the average error decreased between actual and predicted results.

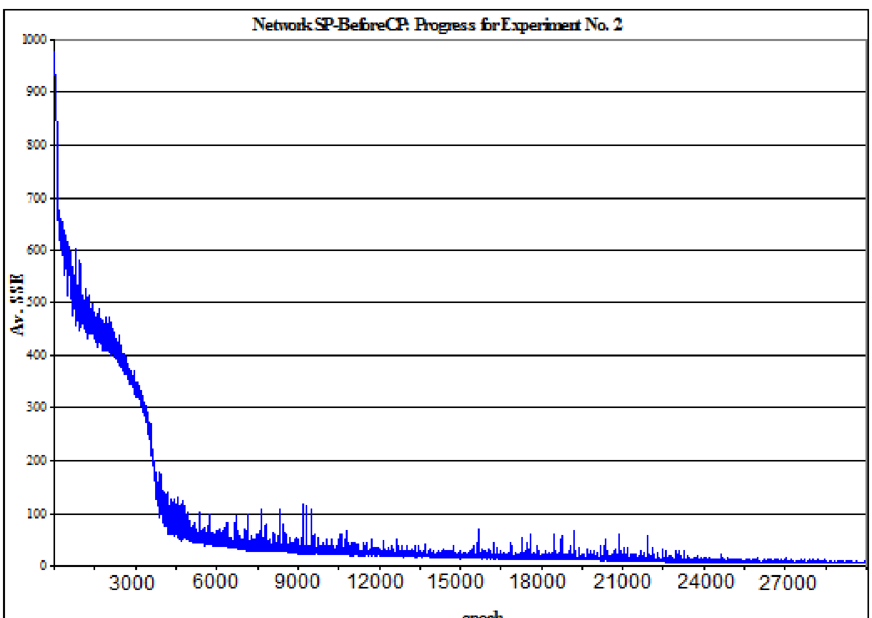

Figure 5: Training progress for experiment no. 2

In all four experiments, it is worth noting that the neural networks settled at the lowest possible training errors that no further significant decrease could be achieved, and the training was stopped when the epochs elapsed reached to the predetermined limit of training cycles (finished by epoch condition). It can also be noticed that in experiments 2 and 6, the network errors obtained were closer to the limit values than those errors obtained in experiments 11 and 16.

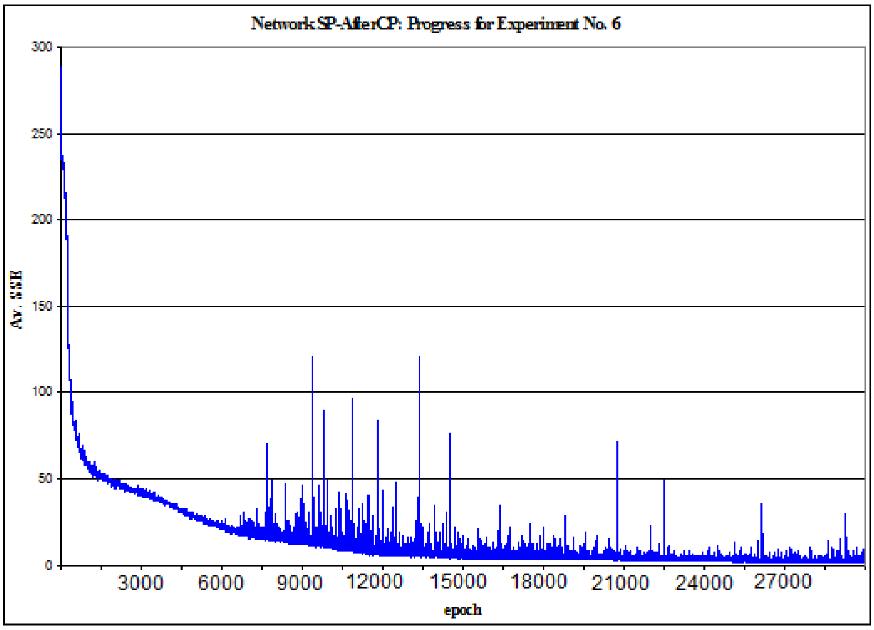

Figure 6: Training progress for experiment no. 6

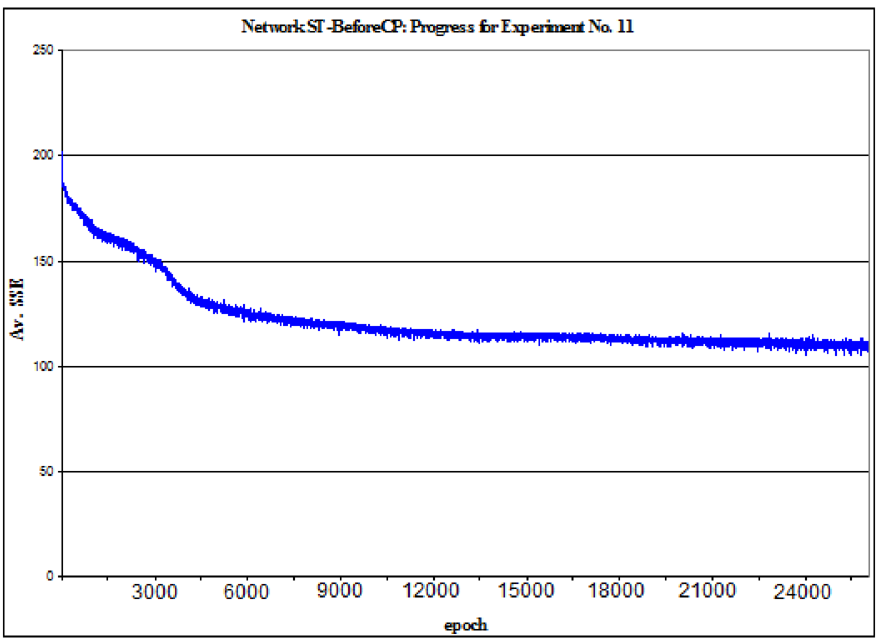

Figure 7: Training progress for experiment no. 11

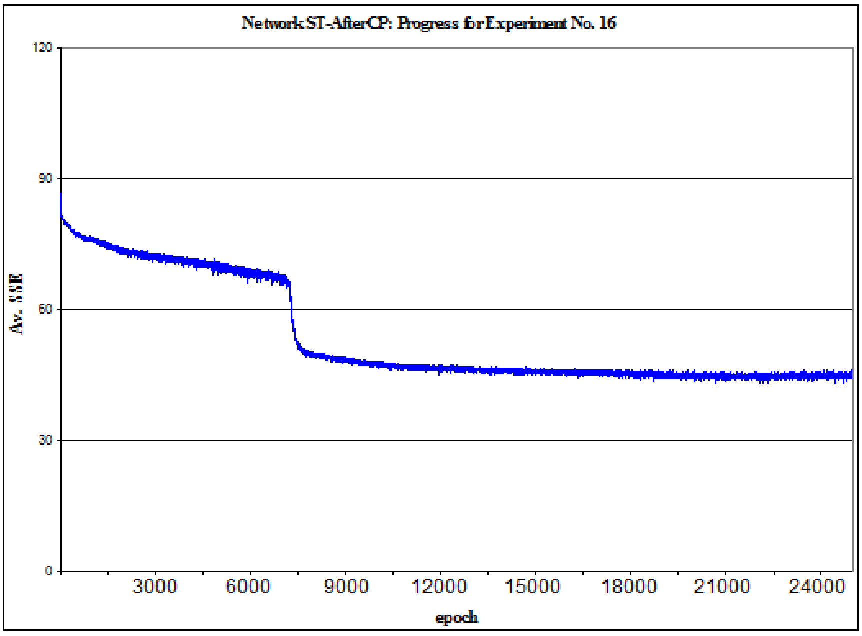

Figure 8: Training progress for experiment no. 16

In order to verify the prediction performance of the developed ANN models and identify the level of learning acquired during training process, the relative difference between ANN and actual outputs were calculated for all training and testing patterns. This was done by dividing the absolute value of the difference between ANN and actual outputs on the actual output value. The resulted value was then multiplied by 100. Training and testing patterns were grouped by their relative difference, as shown in Table (5)

The results presented in Table (5) show that the ANN models of experiments 2 and 6 were properly learned almost 20% of the patterns presented to them (i.e. with no difference between ANN and actual outputs), and almost 75% of the patterns with less than 50% difference. Similarly, the other two models (experiments 11 and 16) were properly learned almost 10% of the patterns presented to them (i.e. with no difference between ANN and actual outputs), and almost 50% of the patterns with less than 50% difference.

Table 5: Summary of patterns grouped by their relative difference

Network	**SP-Before CP (exp. 2)**		**SP-After CP (exp. 6)**		**ST-Before CP (exp. 11)**		**ST-After CP (exp. 16)**	
% of Diff.	Training	Testing	Training	Testing	Training	Testing	Training	Testing
0	89 **(18.5%)**	8 **(15.1%)**	167 **(20.1%)**	16 **(17.4%)**	158 **(8.2%)**	19 **(8.9%)**	522 **(10.7%)**	59 **(10.9%)**
1 to 50	282 **(58.6%)**	27 **(50.9%)**	426 **(51.3%)**	50 **(54.3%)**	815 **(42.2%)**	76 **(35.5%)**	1745 **(35.7%)**	189 **(34.8%)**
50 to 100	101 **(21.0%)**	15 **(28.3%)**	206 **(24.8%)**	22 **(23.9%)**	498 **(25.8%)**	59 **(27.6%)**	1213 **(24.8%)**	142 **(26.2%)**
> 100	9 **(1.9%)**	3 **(5.7%)**	32 **(3.9%)**	4 **(4.3%)**	460 **(23.8%)**	60 **(28.0%)**	1410 **(28.8%)**	153 **(28.2%)**
Total	481	53	831	92	1931	214	4890	543

On the other hand, it can be seen that the ANN models of experiments 2 and 6 were properly predicted almost 15% of the testing outputs (i.e. with no difference between ANN and actual outputs), and 70% of the testing outputs with less than 50% difference. Similarly, the models of experiments 11 and 16 were properly predicted 10% of the testing outputs (i.e. with no difference between ANN and actual outputs), and 45% of the testing outputs with less than 50% difference.

For further evaluation of ANN performance, MLR models were developed for each group of data (*SP-Before CP*, *SP-After CP*, *ST-Before CP*, *and ST-After CP*) using MINITAB 13 statistical package. The coefficients of determination, R^2, for predicted versus actual outputs of ANN and MLR, in training and testing patterns were calculated and summarized in Table (6).

Table 6: R^2 for predicted versus actual outputs of ANN and MLR

Group of Data (Network)	Task	No. of Patterns	Coefficient of Determination (R^2)	
			ANN	MLR
SP-Before CP	*Training*	481	0.994	0.226
	Testing	53	0.988	0.286
SP-After CP	*Training*	831	0.992	0.272
	Testing	92	0.994	0.231
ST-Before CP	*Training*	1931	0.585	0.279
	Testing	214	0.583	0.289
ST-After CP	*Training*	4890	0.598	0.222
	Testing	543	0.475	0.226

When comparing the R^2 values of the ANN versus actual outputs for the same group of data with the corresponding values of the MLR versus actual outputs, it can be noticed that the ANN and actual outputs demonstrated higher statistical correlation than the MLR and actual outputs for all groups of data.

The ANN models for *SP-Before CP* and *SP-After CP* networks showed that they well represented the training patterns with very high statistical correlation ($R^2=0.994$ and $R^2=0.992$ respectively) between the ANN and actual outputs, while the ANN models for *ST-Before CP* and *ST-After CP* networks showed that they represented the training patterns with moderate statistical correlation ($R^2=0.585$ and $R^2=0.598$ respectively) between the ANN and actual outputs. These moderate values of R^2 were due to the large variety of the input patterns.

IMPLEMENTATION OF THE DEVELOPED ANN MODEL

In order to implement the designed ANN model, interactive and user friendly computer software has been developed. The developed software is named; Neuro-WB prediction, an acronym for neural networks wire breaks prediction. Microsoft Visual BASIC (VB6.0) programming language was used for designing and programming the forms and modules (functions) that drive the Neuro-WB prediction software. It was designed to import data patterns and automatically prepare it for training and testing. Two modes for predicting the number of wire breaks were provided: the first mode is to predict wire breaks for a single pipe, and the second mode is to predict the number of wire breaks for group of pipes in one time (batch prediction). Figure (9) shows the architecture of the developed software.

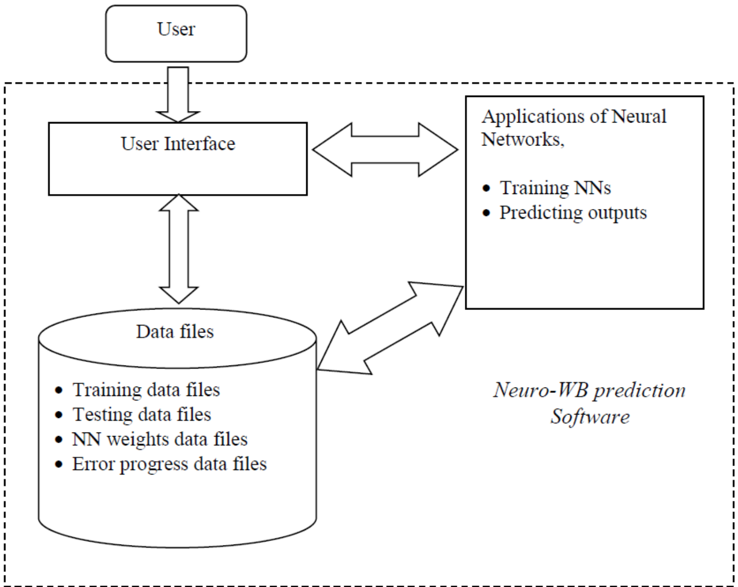

Figure 9: Architecture of Neuro-WB prediction software

When Neuro-WB prediction starts, the Multi-Tab window is displayed. This window provides the user with three main options to use the software. These options are:

- Predict the number of wire breaks for single pipe or batch of pipes.
- Training and testing neural networks, save trained neural networks and open trained neural networks.
- View data patterns used in the training of neural networks.

Figures (10-11) show selected screenshots of Neuro-WB prediction software for illustration.

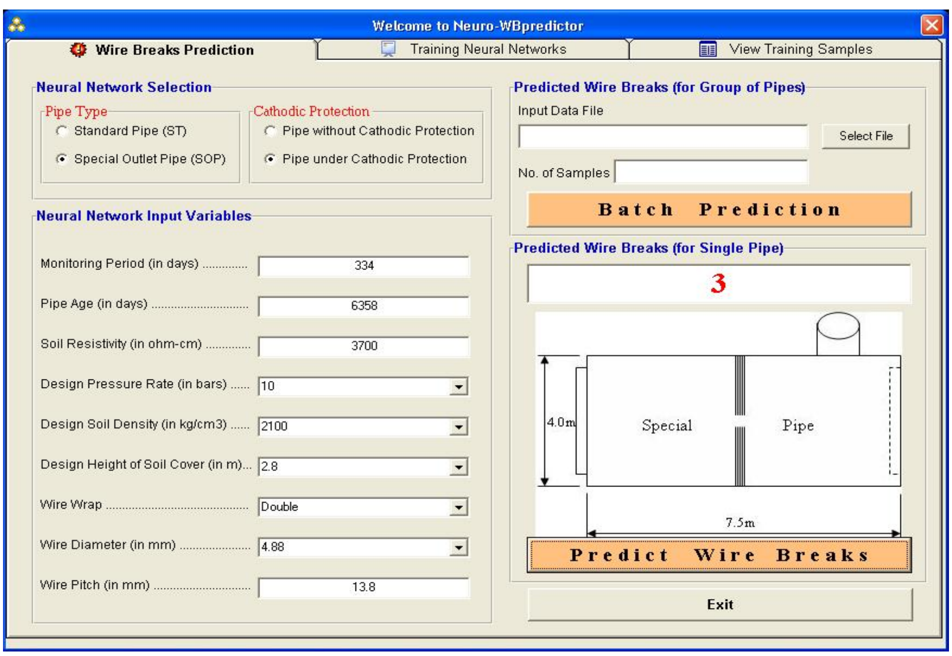

Figure 10: Wire breaks prediction for single pipe

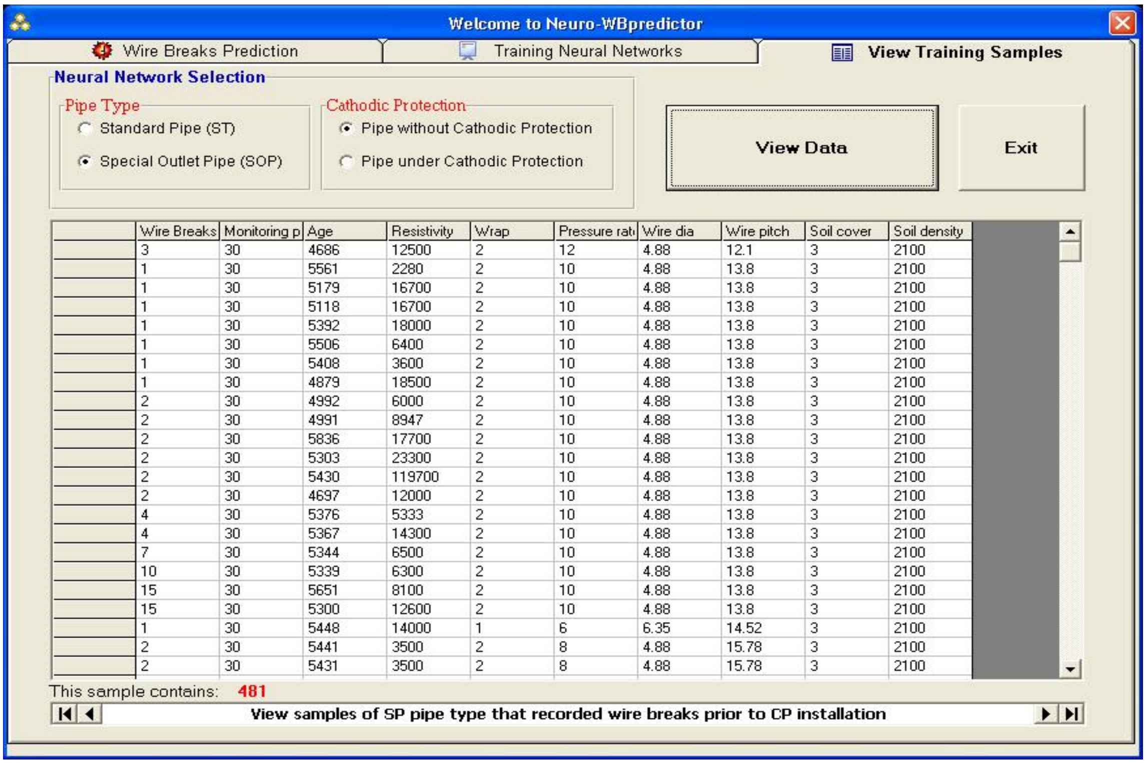

Figure 11: Viewing training samples

CONCLUSIONS

We have studied the feasibility of using ANN techniques to predict wire breaks in PCC pipes and implemented the developed models based on real-world acoustic monitoring data of the MRP in Libya. Various network structures were experimented using Back-Propagation Neural Network (BPNN) training algorithm. Overall, the application of ANN techniques for predicting PCCP wire breaks appears feasible and the prediction performance of good quality. The ANN model has been developed into a software tool named Neuro-WB prediction to enable regular applications of the model. The proposed model will eventually be further integrated into the comprehensive Pipe Risk Management System (PRMS) currently being developed by MRA to help in estimating the rate of deterioration for uncoated pipes and then prioritize inspection and maintenance measures needed to prevent future deterioration and eventual failure of the distressed pipes, which is considered an important function of the PRMS.

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NOMENCLATURE

ANN	Artificial Neural Networks
BPNN	Back-Propagation Neural Network
CP	Cathodic Protection
GPR	Ground Penetrating Radar
MLR	Multiple Linear Regression
MRA	Man-Made River Authority
MRP	Man Made River Project
NDT	Non-Destructive Testing
PCCP	Pre-stressed Concrete Cylinder Pipe
PCI	Pipe Criticality Index

PRMS	Pipe Risk Management System
RFEC/TC	Remote Field Eddy Current/Transformer Coupling
SP	Special Pipes
ST	Standard Pipes