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A Hybrid Prediction Model for Pipeline Corrosion Using Artificial Neural Network with Particle Swarm Optimization

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Abstract: Pipeline corrosion is one of the most critical and severe cause of pipeline incidents annually. Pipeline incidents bring about disastrous damages not only to human but also to the ecosystem and economy of a country. Pipeline operators are aware of this fact and have deployed a more regular and thorough pipeline inspection program through various sensors for data acquisition that can be analyzed to predict the current state of pipelines. However, there are different factors which cause corrosion and current analytical methods are not specific enough in the prediction process. Therefore, a prediction model that is able to target specific corrosion damage mechanisms needs to be developed. Artificial Neural Networks (ANN) have been selected as the most suitable method to be adopted for such model. A critical study done among existing work on ANN has shown the need to improve time efficiency of the method. This project aims to develop a hybrid prediction Model which can target specific corrosion damage mechanisms. The basic ANN Model will be improved by integrating the Particle Swarm Optimization (PSO) algorithm to achieve a better and optimal performance. The final hybrid model will be put to test with a real world industrial dataset to verify its time efficiency as compared to the basic ANN Model.

Key words: Corrosion, damage mechanism, prediction model, artificial neural network, particle swarm optimization, world

INTRODUCTION

According to the American Petroleum Institute, the oil and gas industry is one of the largest and most capital-intensive industries in the world. There are currently more than tens of millions of kilometers of oil and gas pipelines being installed and used daily across the globe (Demma *et al*., 2004; Reber *et al*., 2002). Most of the pipelines in use are made of steel as they deliver the safest means to transport large quantities of oil and gas products. Despite the use of insulation on these steel pipelines, they are still prone to deterioration when exposed to various damage mechanisms over time (Reber *et al*., 2002; Lowe *et al*., 1998). These damage mechanisms, i.e., CO_2 corrosion, cavitation and sulfidation, eventually lead to corrosion and the pipeline is subjected to leakages and ruptures, resulting in major financial losses to the operators and ultimately, pose substantial Health, Environment and Safety (HSE) hazards to the surrounding ecosystem (Singh and Markeset, 2009; Hirao and Ogi, 1999). Knowing this fact, operators have for a long time practiced regular inspection on pipelines to ensure that they operate smoothly and to minimize the risk of accidents (Rose, 2004). These inspections make use of sensors that feed in specific parameters in pipelines and store them in a database. Prediction methods are used to predict and monitor the state of pipelines through the use of this corrosion data to determine preventive actions to be taken ahead of a potential incident. Although, comprehensive measures have been taken throughout the years, pipelines are still failing and pipeline incidents are still occurring throughout the globe, bringing about deadly consequences.

Figure 1 shows the annual total of oil and gas pipeline incidents that happened between the years 1996 to 2015 as collected by the Pipeline and Hazardous Materials Safety Administration (PHMSA) (Anonymous, 2016). Although, there is an intermittent pattern of increase and decline, it can be seen that the overall trend of pipeline incidents is increasing. Pipeline incidents always bring about casualties and it is therefore of paramount importance to have a solid and good way to monitor and predict the state of oil and gas pipelines. A detailed breakdown of pipeline incidents in the last recorded year, 2015 is shown in Table 1.

From Table 1, it is seen that corrosion has accounted for 16.9% of the total number of incidents, scoring the second highest percentage right behind material failures.

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Fig. 1: Count of pipeline incidents from years 1996-2015 (Anonymous, 2016)

Table 1: Breakdown of pipeline incidents by cause in the year 2015 (Department of transportation, 2016)

Cause	Number	Percentage	Total cost ($)
Excavation	69	9.9	15,521,210
Corrosion	118	16.9	166,081,880
Incorrect operation	56	8.0	3,749,971
Material failure	298	42.6	55,023,110
Natural forces	45	6.4	15,592,424
Outside forces	49	7.0	18,915,064
Other causes	65	9.3	48,311,897
Total	700	100.0	323,195,546

Despite being second in terms of percentage caused, corrosion incurred the highest total cost as compared to all other causes, at an economic cost of $166,081,880 in the year 2015 alone.

According to the US Department of Transportation's Research and Special Programs Administration, Office of Pipeline Safety (RSPA/OPS), the percentage of corrosion-related pipeline incidents averages around a quarter or 25% of the total global number of incidents annually (Anonymous, 2016). During an expert interview with Staff Corrosion Engineer from a Malaysian oil and gas company (ILLC., 2016) he agrees with the statistics, adding on that in Malaysia, pipeline corrosion is more severe and accounts for over 35% of pipeline failures and incidents.

The statistics show that the current corrosion prediction methods used in the oil and gas domain have not yet been able to address the problem of corrosion. Thus, there is a necessity to develop an improved prediction model for corrosion that overcomes the gaps found in the existing methods.

Literature review

Corrosion data: Unlike most industries, the oil and gas industry has for a long time dealt with large quantities of data to make technical decisions including the monitoring of pipeline health. The use of ultrasonic waves is the most popular way to do so. Ultrasonic sensors are installed at certain sections of pipelines to collect measurements on the thickness of the pipeline wall to determine the current corrosion rate (Veiga *et al*., 2005; Krautkramer and Krautkramer, 2013). Besides, various other environmental parameters in which the pipeline is exposed to are also collected (ILLC., 2016). Collectively, they can be referred to as corrosion data and can be fed into algorithms which predict the rate of corrosion (USDT., 2016).

Despite having an extensive collection of data, models today are still unable to target specific damage mechanisms that cause pipeline corrosion. As a result, current analysis and identification of damage mechanisms still depend wholly on human experience and knowledge (Singh and Markeset, 2009; Veiga *et al*., 2005). The models today have limited accuracy because relevant parameters leading to specific damage mechanisms are not targeted specifically. Besides, some organizations have only limited knowledge about the real properties of corrosion and are currently making assumptions about its nature (USDT., 2016; Supriyatman *et al*., 2012).

Hence, the currently available corrosion data in the industry have not been fully and extensively utilized due to the lack of good prediction models. The inferior analysis provided by current corrosion prediction models should not be overlooked as the oil and gas industry is categorized under "high risk" or "high priority" and even a little margin of error in the predicted result can lead to major consequences (Black and Baldwin, 2012).

Corrosion prediction methods: After reviewing and comparing the existing prediction methods in Table 2 ANN is selected to be the method of focus and the model to be applied for this research. As mentioned in study, the complex nature of corrosion makes modelling of damage mechanisms hard and therefore, the ability of ANN to model complex relationships is highly beneficial to the research. Besides, ANN will also offer flexibility in terms of the type of predicted output because it can be used to predict various forms of output for the corrosion data. For instance, it can provide a precise numerical output when the rate of corrosion needs to be predicted, a classifier output when the severity of corrosion needs to be predicted and finally a probabilistic output when the probability of corrosion or failure needs to be predicted.

The dependence of this project on reliable input data should not be of concern as the dataset for this project will be obtained from a Malaysian oil and gas company and Universiti Teknologi PETRONAS (UTP)'s Centre of Corrosion. Therefore, ANN which performs the best with a reliable dataset is suitable to be used. However, the ANN Model will need to be backed up using several other optimization techniques or algorithms in order to overcome its disadvantages in terms of long training time and poor time efficiency.

Table 2: Comparison between existing prediction methods in the oil and gas domain

Prediction model	Fault tree analysis	Mechanistic model	Artificial neural network
Reliability on data	Low	High	High
Training time	Low	Very high	High
Accuracy	High	Very high	Very high
Advantages	Uses knowledge of expert human operators	It is the result of thorough and comprehensive experimentation	Capable of representing complex forms of relationships Good to represent non-linear relationships Flexible
Disadvantages	Limitations of the human knowledge A long time may be needed to design the fault tree	Requires understanding of the underlying chemical, electrochemical and transport processes A long time is needed to produce a reliable model for a single DM	Dependent on reliable input data Long training time Long training time/low efficiency

Table 3: Comparison between existing works on ANN

Researchers	Type of predicted output	Gaps found	Suggested future work
Supriyatman *et al.* (2012)	Numerical Long training time/low time efficiency	Selection of topology is done manually	To have a better research that identifies the related parameters
Ren *et al.* (2012)	Numerical	Selection of topology is done manually	--
Sinha and Pandey (2012)	Probability Long training time/low time efficiency	Selection of topology is done manually	Reduce training time

Table 3 shows the comparison between three existing works on the ANN Model for prediction in oil and gas domains. A recent research by Supriyatman *et al.* (2012) and Ren *et al.* (2012) has proven that ANN is a suitable model to be implemented in the oil and gas domain as it demonstrates a high accuracy in predicting complex relationships. The result of this research is also supported by Ren *et al.* (2012), Sinha and Pandey (2002) whose researches have proven that non-linearity in the variables used in their experiments are accurately represented by ANN.

From the papers studied, all three researches Supriyatman *et al.* (2012), Ren *et al.* (2012), Sinha and Pandey (2002) state that the selection of neural network topology is done manually. Another problem is the long training time or low time efficiency of the ANN Model (Supriyatman *et al.*, 2012; Sinha and Pandey, 2002). ANNs have a long training time due its nature of learning from historical dataset. As the number of training epochs is increased, the error of the network decreases, the accuracy of prediction increases but at the cost of a longer training time.

Both of the problems show an area in the ANN that can be improved. A study by Koehn (1994) has shown that different network topologies affect how fast the network learns.

Figure 2 shows how different topologies achieve different error rates after a certain number of epochs. Each of the 4 lines represents a unique topology and from (Fig. 2), it can be seen that the 5-node fully connected topology achieves lower error rates at the same number of epochs when compared to the other 3 topologies. Since, different topologies achieve a minimum error rate at different number of epochs, it means the time needed to train the models varies as well. Thus, it is possible to implement a form of selection or optimization algorithm that is able to perform selection of an optimal network topology using ANN as the fitness function instead of a manual selection (Koehn, 1994).

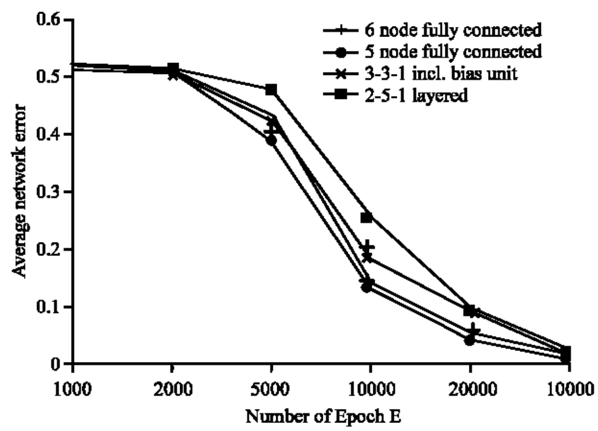

Fig. 2: The comparison between different network topologies with the average network error achieved (Koehn, 1994)

The researchers have also proposed several suggestions for future research such as to have a better research that identifies the related parameters to be fed into the neural network (Supriyatman *et al.*, 2012) and to reduce the training time needed (Sinha and Pandey, 2002). The first suggestion to identify the related input parameters matches the motivation for this research, which is to target specific damage mechanism by focusing on the right parameters that relate to them. The second suggestion to reduce the training time can be addressed by implementing the optimization algorithm to select an optimal ANN topology.

Table 4: Comparison between GA and PSO

Parameters	GA	PSO
Ability to reach good solution without local search	Lower	Higher
Influence of optimal solution on population	Lower	Higher
Continuity of search space	Lower	Higher
Influence of population size on solution time	Exponential	Linear

Different optimization algorithms will have to be compared to identify which one to be implemented to optimize the basic ANN Model. Optimization, in this research will refer to the improvement in time efficiency of the model. It will be represented by the time taken to train the ANN to reach a certain level of prediction accuracy. The longer the time taken to train the ANN, the lower its time efficiency.

Optimization algorithms: The two most commonly used optimization algorithms, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been studied. The results of the comparison between the two algorithms are shown in Table 4.

Based on Table 4, by Kachitvichyanukul (2012) it can be seen that PSO outperforms GA in these four parameters: ability to reach good solution without local search, influence of optimal solution on population, continuity of search space and influence of population size on the solution time which are relevant to this research. Firstly, PSO has a higher ability to reach a good solution without performing local search, unlike the GA, thus lowering the time needed for the search. This is due to the lower continuity of search space in GA which may render it incapable of producing all potential solutions in the search space.

Furthermore in PSO, the optimal solution has a higher influence on the population as compared to GA. For simpler optimization problems such as the ANN topology, this helps to save searching time as the subsequent iterations will revolve around the optimal solution found.

Another research proved that the PSO exhibited computational efficiency superiority over the GA with a 99% confidence level (Hassan *et al*., 2005). This has shown to be in line with the results obtained by Kachitvichyanukul (Kachitvichyanukul, 2012) because the influence of population size on the solution time is exponential in GA as compared to PSO. Hence, the time taken by GA will always be longer and might not be suitable for this project where time efficiency is a factor that needs to be improved.

Novelty of research: From the literature study of existing methods and researches, the novelty for this research is twofold. Firstly, there are no existing prediction models that are able to target specific damage mechanisms that affect pipeline corrosion and existing methods make their prediction without regards to these damage mechanisms. Secondly, I will be establishing a novel algorithm that optimizes both ANN topology selection and also ANN training, to improve time efficiency of the whole model.

Problem statements: There are problems with existing prediction models for pipeline corrosion in the sense that they are not yet able to target their prediction towards specific damage mechanisms that cause corrosion. The current models are generalized models that target the entire corrosion data as a whole. By having a specific instead of generalized prediction, the prediction shall have a higher accuracy and confidence level. Besides, the ANN models that have been developed for corrosion in oil and gas pipelines have a low time efficiency and this can be improved by optimizing the network topology for the ANN model to have a shorter training time. The following Research Questions (RQ) are extracted from the research problems:

- [RQ1]; What are the parameters that are relevant to the damage mechanisms focused in this research?
- [RQ2]; How can a hybrid prediction model be developed by leveraging on PSO to optimize the ANN model?
- [RQ3]; How will the proposed hybrid model be able to achieve a higher time efficiency?

Objectives: The following objectives are outlined to address the research problems:

- To conduct a critical study on damage mechanisms for pipeline corrosion and thus identify the parameters that are related to the focused damage mechanisms
- To develop a hybrid prediction model based on ANN and optimized using PSO
- To evaluate the performance of the proposed hybrid model to achieve a higher time efficiency

MATERIALS AND METHODS

Research methodology: Figure 3 shows the methodology for this project. Firstly, the obtained corrosion dataset will be pre-processed to suit the ANN Model. Under data-preprocessing, the corrosion data is first normalized and then segregated into training data and validation data. The training data will be used to train the ANN, while the validation data is used to validate the performance of the ANN. These data will then be fed into the Particle Swarm Optimization, using Artificial Neural Network (ANN) training time as the fitness function, to select an optimized ANN topology. An optimized ANN

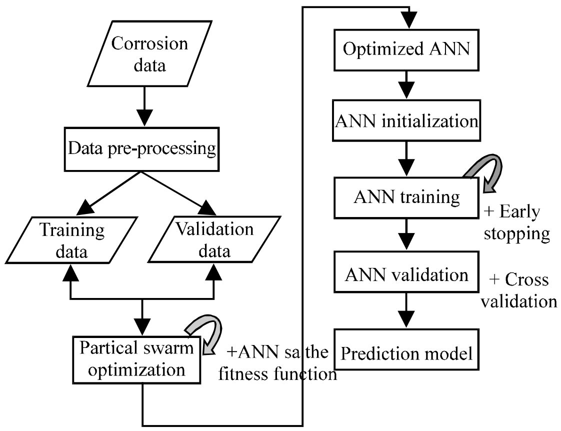

Fig. 3: The flow of research methodology

topology refers to a topology that exhibits a higher time efficiency compared to a topology that is selected manually. The ANN will be initialized using the optimized topology along with other ANN parameters.

The optimized ANN Model will be trained using the same training data until a certain condition is met. Early stopping, a method to prevent the network from overfitting will be used by stopping the training once the network error recorded is higher than its previous reading. Once successfully trained, the ANN will be validated against the validation data to determine its time efficiency. The final outcome will be the hybrid prediction model that is able to target specific damage mechanisms for pipeline corrosion.

Proof of concept

Data preparation: The synthetic dataset has been obtained through a literature survey (Tong, 2015; Ossai, 2012; Papavinasam *et al*., 2013) and has been verified by a Staff and Senior Corrosion Expert (USDT., 2016; ILLC, 2016) to fulfil actual industry standards and validated for use in this proof of concept. The dataset synthesizes 300 rows of cross-sectional data, obtained from sensors attached to different points on different pipelines, at the same point in time as shown in Fig. 4. Cross-sectional data refers to widely dispersed data relating to one period of time or without respect to variance due to time.

Figure 5 shows some sample rows of the synthetic dataset. The dataset is a supervised dataset and comprises of pairs of input as well as the output. Each row of the data consists of 3 input parameters: CO_2 partial pressure (MPa), flow velocity (m/sec), temperature (°C) and a classifier output that classifies the severity of corrosion, either it is within: "Acceptable" range, "Normal" range or severe "Corrosion". The relationship

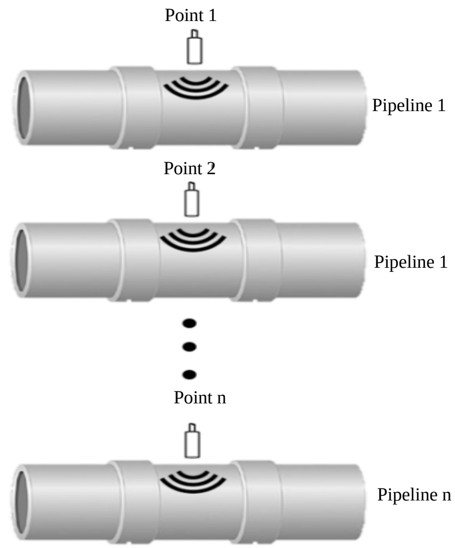

Fig. 4: The synthetic data synthesizes data collected from different points from different pipeline at certain point in time (Tong, 2015)

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0.3661,2.8272,62.8546,corrosion.
0.1360,2.9751,46.6364,normal.
0.4472,1.2772,48.6372,acceptable.
0.3175,2.2537,64.8342,corrosion.
0.0732,3.1334,45.7246,normal.
0.5120,1.1260,47.9506,acceptable.
0.3703,1.8825,66.2243,corrosion.
0.1179,2.8100,51.0876,normal.
0.4992,1.1150,53.3068,acceptable.
0.3417,2.0103,61.9454,corrosion.
0.1160,3.1569,47.8357,normal.
0.4613,1.1931,52.2789,acceptable.
0.2614,1.8044,64.3008,corrosion.
0.0893,3.3629,47.2793,normal.
0.4130,1.5023,49.0257,acceptable.
0.5837,2.1303,65.4294,corrosion.
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Fig. 5: Some sample rows of the synthetic dataset (Tong, 2015)

between the inputs and outputs are non-linear and represent the actual nature of corrosion in subsea pipelines (Tong, 2015).

Assessment model: Figure 6 shows the initial ANN model developed for the proof of concept. It is a feed-forward Multi-Layered Perceptron (MLP) which is trained using Back-Propagation (BP). The model comprises of an input layer with 3 nodes a hidden layer with 3 nodes and also an output layer with 3 nodes. Each node in every layer is connected to every node in the following layer, creating a topology with 18 connections or weights. Table 5 shows the parameters of the ANN Model and justifies the reasoning behind the initialized values.

Table 5: Initial parameters, values and justifications

Parameters	Values	Justification
Input nodes	3	The data contains 3 predictors
Output nodes	3	The output has 3 possible outcomes
Hidden nodes	3	Based on literature study
Hidden layers	1	Based on literature study
Initial weights	Between 0-1	Based on literature study
Learning rate	0.2	Based on literature study

Objectives: The objectives of this proof of concept are:

- To prove the ability of ANN to map non-linear relationships in pipeline corrosion data by obtaining a high accuracy in prediction
- To prove that ANN is able to improve its prediction accuracy by trading off its time efficiency

Procedures: The procedures involved in this proof of concept are the synthetic data set is first normalized into values between 0 and 1. The normalized data is divided into training set and validation set in the ratio of 7:3. The training set thus contains 210 rows of data per epoch while the validation set contains 90 rows of validation data. The training and validation sets are sampled in 3 in different ways. Set A is sampled from the beginning of the dataset, set B from the end of the dataset and set C from the middle of the dataset. This cross-validation reduces bias in the results and improves confidence in the model. The ANN is trained thrice on each data set, with 50 epochs, 500 epochs and finally 1,500 epochs. The 50, 500 and 1,500 are arbitrary values used to represent low amount of training, medium amount of training and high amount of training. The average accuracy of classifying prediction and also average training time for the 3 tests with 50, 500 and 1,500 epochs are recorded.

RESULTS AND DISCUSSION

Table 6 shows the results obtained for the 3 tests with 50, 500 and 1,500 epoch. From the table, it can be seen that the average accuracies of the model at 50, 500 and 1,500 epochs are 70.00, 97.41 and 98.52% respectively. On the other hand, time taken for the training are recorded at 1.98, 21.33 and 63.27 sec, respectively. A graphical view of the tabulated result will be shown in Fig. 7.

From Fig. 7 it can be seen that the ANN is successful at producing predictions of a high accuracy on non-linear corrosion data that was validated by Corrosion Engineers from a Malaysian oil and gas company. After 1,500 epochs of training, the prediction accuracy of the model has reached 98.52%. The prediction accuracy is very high and has met the first objective of this proof of concept which is to prove the ability of ANN in mapping out non-linear relationships in pipeline corrosion data. This is crucial because the ANN will be used on actual industrial data which also exhibits non-linearity and a high prediction accuracy proves that ANN is a feasible model to be used in this research.

Table 6: Results obtained for the proof of concept

Variables	----------------Values-----------------------		
No. of epochs	50	500	1,500
Total no. of training data	31,500	315,000	945,000
Total no. of validation data	270	270	270
No. of correct prediction	189	263	266
No. of wrong prediction	81	7	4
Accuracy of prediction	70.00%	97.41%	98.52%
Average training time	1.98 sec	21.33 sec	63.27 sec

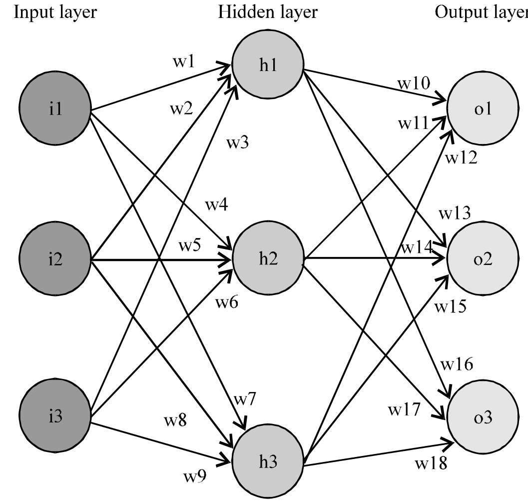

Fig. 6: ANN model used for the proof of concept

It can also be seen that the training time increases linearly as the number of epochs increases. Since, the training time represents time efficiency in this research it can be said that time efficiency decreases linearly as the number of epochs is increased. Besides we can see that the prediction accuracy of the model increases logarithmically as the epochs are increased. A logarithmical growth is depicted by a growth that starts off rapidly, followed by slowed growth that continues to increase at a low rate.

Hence, from Fig. 7 it can be concluded that as the prediction accuracy of ANN increases, the time efficiency decreases. This fact has met the second objective of this proof of concept which is to prove that ANN is able to improve its prediction accuracy by trading off its time efficiency. Although, it may seem that the training time of ANN is not significant from the results of the proof, it is important to note that the size of the synthetic data is much smaller than an actual industrial dataset. In an actual industrial dataset, every epoch will take up more data which translates to an increased training time ((ILLC, 2016).

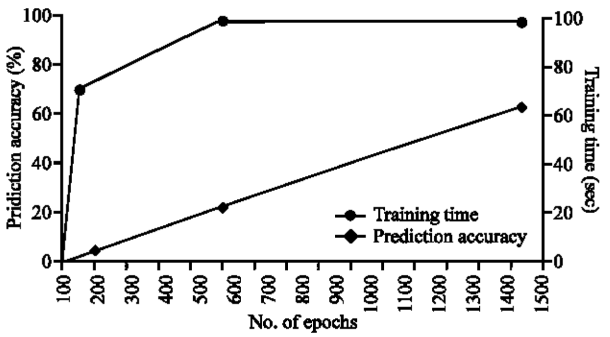

Fig. 7: Graph showing the increase in prediction accuracy and training time as the number of epochs increases

Thus, the proposed methodology in study to have an optimization for the neural network topology using PSO to improve its time efficiency is strongly supported. The logarithmic growth shown by the increase in prediction accuracy justifies the reason to optimize the network because the slower increase in prediction accuracy at later stages of training will take up more training time when trying to train the ANN to an intended level of accuracy.

Therefore, the hypothesis of this research is PSO can be used to find an optimal network topology that learns faster by using capitalizing on the early rapid growth of the logarithmic curve. In this way, only a little time will be spent on the PSO while saving up more time on the actual training of the ANN (Swarm Intelligence, 2015).

CONCLUSION

This review study has studied problems relating to the severity of pipeline corrosion and current prediction models. The pros and cons of several famous models used in the prediction of corrosion in the oil and gas domain were presented. ANN is chosen as the model to be adopted and to be improved in this research. However, the gaps of the ANN Model, i.e., the manual selection of network topology and the long training time resulting in poor time efficiency need to be addressed in later stages of research. It was discussed how optimizing the neural topology may help to solve the stated problems. Through critical study, PSO has been chosen as the potential optimization algorithm to be used to select an optimized ANN topology.

The novelty of this project have been identified via the literature study and several research questions have been determined. Objectives for this research have been detailed as: to conduct a critical study on damage mechanisms for pipeline corrosion and thus identify the parameters that are related to the focused damage mechanisms, to develop a hybrid prediction model based on ANN and optimized using PSO and to evaluate the performance of the proposed hybrid model to achieve a higher time efficiency

An initial proof of concept was conducted to prove the feasibility of ANN to be used in this research. The combined results from the proof and literature study have shown that an optimized topology would allow the model to be trained faster while at the same time, provide an accurate prediction related to the state of pipelines. It is also equally important to target the right parameters that relate to specific damage mechanisms. With the right parameters and input, the ANN will be able to make predictions of a higher accuracy and confidence level.

This next phase of research work will consist of optimizing the ANN model using PSO and identifying the right way to apply PSO to select a network topology which increases time efficiency of the ANN. Finally then, the proposed hybrid model can be put to training with the industrial data set to develop a prediction model that could be highly beneficial to the oil and gas industry.

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