Burst Pressure Strength of Corroded Subsea Pipelines Repaired with Composite Fiber-Reinforced Polymer Patches

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Abstract

To repair corroded subsea pipelines, composite fiber-reinforced polymer (CFRP) patches are often attached to the defected area. The aim of this paper is to present a method to assure if the strength of repaired subsea pipelines is sufficient enough to sustain burst pressure loads. A computational model for predicting the burst pressure strength of repaired pipelines with CFRP patches is presented. An algorithm of artificial neural networks (ANN) is applied. The geometry of corrosion damage is defined by three physical parameters, namely length, width and depth. The computational model is validated by comparison with refined finite element method solutions. The proposed method will be useful for developing a quick procedure for the CFRP based repair scheme of corroded subsea pipelines.

***Keywords**:* Corroded Subsea Pipelines; Repair Scheme; Composite Fiber-Reinforced Polymer (CFRP) Patches; Burst Pressure Strength; Artificial Neural Networks (ANN)

1. Introduction

The integrity and stability of pipelines is the highest priority of the oil and gas industry due to their significant contribution to the economy, environment, and human life as well as its catastrophic consequences in the unfortunate event of failure or mismanagement. In the early development of the oil and gas industry, pipelines were constructed from wooden pipes before it undergoes various evolution in chemical composition and manufacturing processes, which eventually replaced by steel pipes since 1920 to the present day [1]. The history of offshore system failures and incidents have caused significant and disastrous effects to the environment, such as the 2003 Khanty-Mansiysk pipeline oil burst in Russia and the Deepwater Horizon oil spill in the Gulf of Mexico in 2010 [2]. The effects of the incident severely impacted the food chain of sea life population and worst to come, which could cause the extinction of endangered species in the future. In terms of the economic outcome, corrosion problems in offshore structures would result in heavy financial loss reaching over USD 170 billion per year in the United States alone [3]. It may contribute to the shutdown of the pipelines services that affects the total production as well as increase the maintenance and operation costs.

Realizing the essential state and security of oil and gas pipelines, government authorities have engaged proactively in supporting the development of offshore technologies. Since then, the rapid growth of oil and gas technology has led to increased productivity with minimal system failure through the implementation of advanced and effective prevention methods [4]. In addition, oil and gas engineers have become more cautious to ensure the sustainable operation of the pipeline system by developing predictive models to support the currently established repairing methods. The data generated could assist engineers to produce a more efficient design that provides a suitable platform for early preventive measures prior to the failure of the system. The output analysis of the developed models would also facilitate researchers to deliver a more effective repair mechanism with high resilience and better durability, specifically for offshore pipelines systems.

To date, the rehabilitation of corroded subsea pipelines is one of the highly active offshore engineering topics. Among the most significant current discussions for the rehabilitation approach is the application of Composite Fiber-Reinforced Polymer (CFRP) to these offshore risers [5]–[7]. There have been several studies that highlighted the advantage of using CFRP in the literature. For instance, Wang *et al.* [8] addressed the unique properties of CFRP materials that makes them applicable in subsea oilfields, including low weight, high specific strength, high specific modulus, fatigue resistance, corrosion resistance, and low thermal expansion coefficient. Meanwhile, Liew and Green [9] described the function of composites materials to sustain and redistribute the stresses and loads applied to the pipe, tank, or concrete structure of the pipeline system. In another study, Elchalakani *et al*. [10] demonstrated that adhesively bonded CFRP significantly increased the total flexural and bending strength capacity of the pipe, as shown in **Fig. 1**. The study successfully improved the load-bearing capacity of the pipe up to 97% for the rehabilitation series and 169% for the strengthening series.

Fig. 1. Rehabilitation of corroded steel pipelines specimens [10]

Extensive research in offshore engineering has led to the implementation of the Artificial Neural Networks (ANN) in corroded subsea pipelines, which have been carried out by many researchers [11]–[13]. The primary focus of these studies was to identify the cause of the corrosion, failure mechanism, and predicting the corrosion stage. The developed models were intended to predict or determine most of the corrosion-related factors, such as the corrosion rate and leakage behaviour. Senouci *et al*. [14] and El-Abbasy *et al*. [15] created a model that forecasted the potential breakdown of oil pipelines based on various factors other than corrosion through ANN. Meanwhile, Xu *et al*. [16] and Chen *et al*. [17] developed a prediction ANN model solely from finite element analysis of corroded pipelines data. Additionally, Mahil *et al*. [18] took a different approach using ANN to determine and predict the crack growth in aluminium composite materials and Wen *et al*. [19], proposed a model to evaluate the dependability of corroded pipes using two consecutive inline inspections to anticipate the corrosion rate based on the physical properties of the pipeline. He demonstrates the comparison of the trained ANN model to the Monte-Carlo simulation where the suggested ANN modeling is more beneficial in terms of time analysis and pipelines reliability prediction. It should be noted, that are reported in the open literature above, for a more precise and accurate study result could only be obtained through comprehensive data and detailed analysis to detect specific parameters and behaviour of the pipelines

Based on the aforementioned investigations, numerous studies and methods have been explored and conducted related to the corroded risers and the ANN platform. However, fewer attempts have been performed to develop an effective prediction model that correlates the ANN with the repaired assessment method, particularly using CFRP. A conceptually identical work that proposed a similar method was carried out through the development of the ANN platform to predict the absorbed energy in the composite panels at low speed [20]. Therefore, the main objective of this study is to predict the burst pressure and assess the suitability of CFRP repaired assessment to multi-level corrosion in subsea pipelines using the Finite Element (FE) analysis and ANN modeling. The American Petroleum Institute (API) type X42 steel pipeline and rehabilitating materials, as suggested by Leong *et al*. [21], were the focus materials in this research. Initially, a set of numerical models was generated using the API 5L type X42 steel pipelines comprising a variety of corrosion levels with varying geometries defect between them. Following that, the rehabilitated pipes data set were modeled using FE analysis and the results were compared to the experimental data acquired from previous studies [5], [22] for validation purposes. A detailed parametric analysis was conducted to ascertain the effect of defect shape to the composite materials and the burst pressure of corroded pipelines. Lastly, the validated FE data were used to develop an ANN model to forecast the burst pressure based on various combinations of input categories. The proposed method in this article may be used to assess the reliability of enhanced CFRP structural repaired systems at different corrosion levels and defect size.

2. Methodology

In this study, the type of corrosion focused is localised or pitting corrosion that occurs on the outer surface of the pipelines. The corrosions which occurred over the years mainly due to the corrosive environment of seabed will cause the pipes to crack and leak by the burst pressure of transportation liquid or gas petroleum. The methodology was divided into three main phases. Phase 1 discussed the input data for the FE and ANN models. Phase 2 involved the process of FE modeling and end with Phase 3 by the development of ANN prediction model using the input data. The efficacy of the suggested method was demonstrated by comparing the output of the ANN with the historical FE output. **Fig. 2** shows the flowchart of the research methodology.

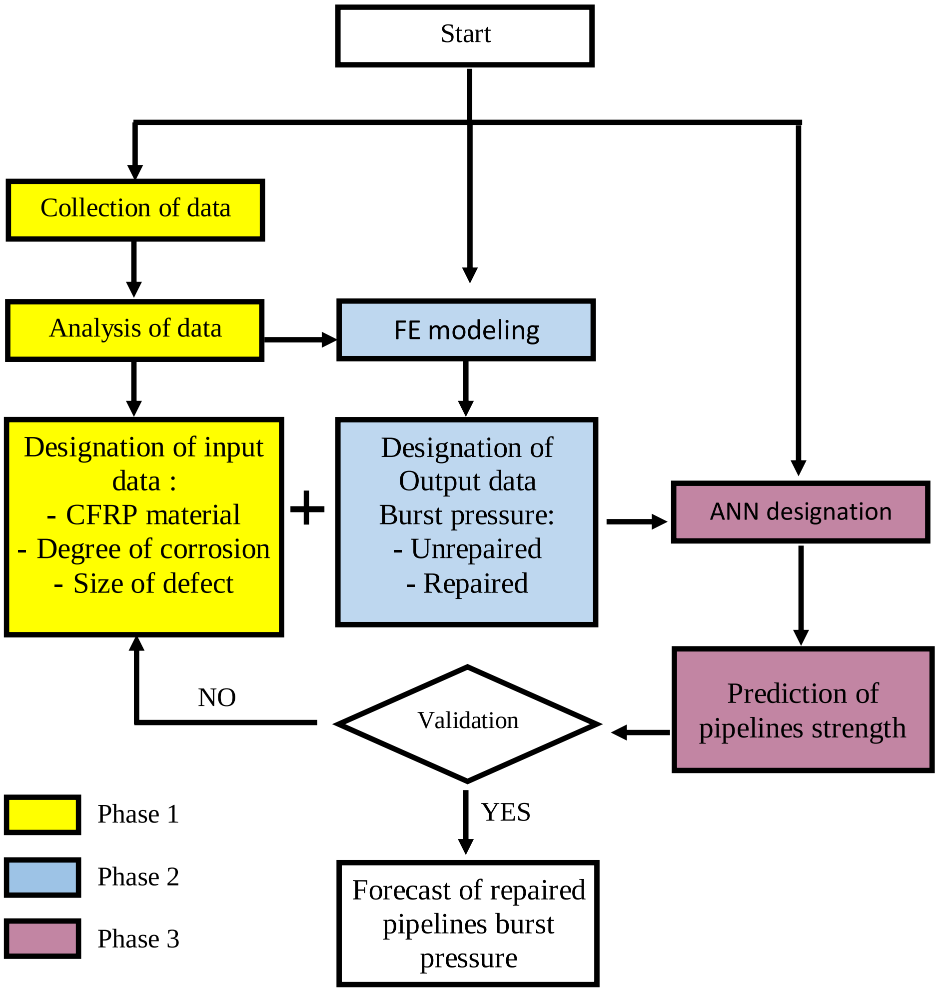

Fig. 2. Research flow diagram of the present study comprising three main phases

2.1. Procedure for CFRP-based Repair Scheme of Corroded Subsea Pipeline

CFRP is a potential material for the rehabilitation and reinforcement of subsea pipelines due to its various unique properties. The low density of CFRP allows the wall section material to be thinner than the main steel pipe body and reduce the weight to carry on deck, thus, decreasing the repairing cost. Furthermore, the excellent corrosion resistance of CFRP removes the need for additional coating or protection during the installation phase. There are variety of reliable methods available for the application of CFRP to the corroded pipelines and this study focused on the method proposed by these three articles [5], [10], [23].

Generally, CFRP is a combination of two materials, called putty and composite wrap. The putty or grout is used as the infill material at the defected area caused by corrosion or gouging. The material functions to provide a smooth bed for the composite wrap and serves as a medium for load transfer from the corroded surface to the composite wrap [5]. Therefore, minimizing the radial distortion and transferring stress from the pipe to the outside shell. Next, the composite wrap is applied to the designated section where it is usually made of polymer or plastic matrix reinforced with fiber to provide very high strength and stiffness bonding [24]. **Fig. 3** illustrates the application of the CFRP to the steel pipeline [5]. A typical standardized procedure for CFRP application begins with the cleaning of the defected area of the pipeline before applying the putty to fill the damaged section. Then, the composite wrap is used to wrap the whole damaged section in several layers depending on the design criteria to achieve the desired strength.

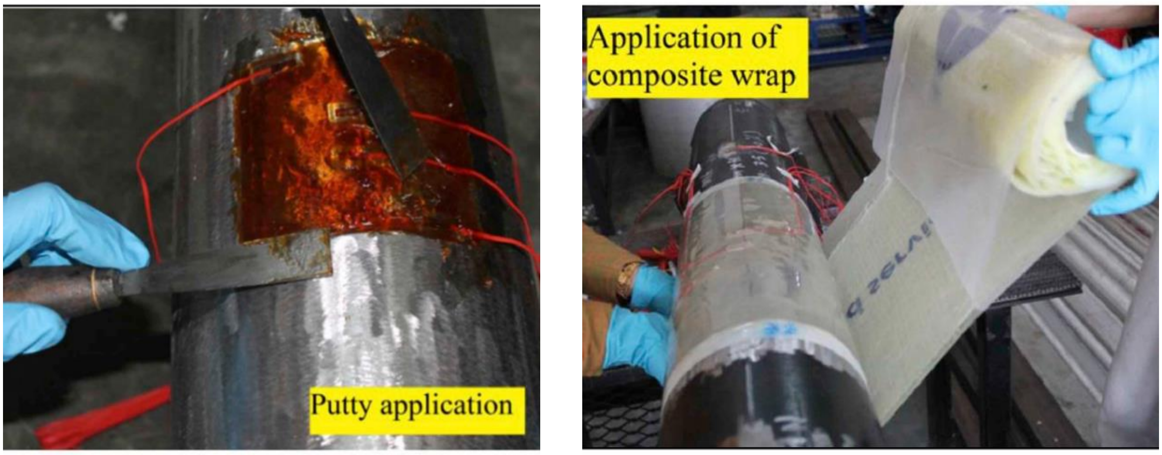

Fig. 3. Process of putty and composite wrap application to the steel pipeline [5]

The term "putty" refers to the type of substance used to correct the surface imperfections of the pipeline, which is commonly composed of epoxy resin, before applying the composite wrap. In addition, metallic or mineral fillers are utilized to alter the putty's mechanical, curing, and shrinkage qualities. For example, the internal/burst pressure borne by the pipe at the repaired section, would be transmitted and shared by the outer composite wrap via the infill material. The composite material serves as the principal load-bearing component in the repair section, while the putty material acts as a vital bridge to ensure smooth load transfer. The sequence of the aforementioned repaired methods was used as a reference to design the models for the FE analysis.

2.2. Data input

Two input data were considered to develop the desired models. The first data set consists of the historical inspection data obtained from a local oil company in Malaysia. The data recorded the change of physical outer surface properties (length, width and depth) of the subsea pipelines due to corrosion. The following information in **Table 1** [25] pertains to the properties pipeline study and their operational data. This data was used to validate the ANN modeling in the last stage of this study. The second data set was designed to mimic the defective area on the pipelines, which varies in length, width, and depth. The corrosion level was set between 15% to 80%, which were determined by statistical analysis of historical inspection data [25]. A broad range of data is needed for the ANN modeling to be trained and function effectively. The data also were combined with the putty and wrap data to form a composite repaired, as suggested by Azraai *et al*. [26] and Leong *et al*. [21]. The detail of the composite is shown in **Table 2**[21] consisting combination of infills (putty) and composite wrap A. A single square shape is considered for the defect shape in this study as shown in **Fig. 4.** The residual burst pressure of each pipeline is determined before and after the composite is applied. The data later used as the training data for the ANN prediction model.

Table 1. General information of the targeted pipelines [25]

Parameter	Unit	Detail
Type of structure	-	Gas pipeline
Outer diameter	mm	168
Wall thickness	mm	9.5
Total length	m	2543.53
Age	Year	19
Material grade	-	API 5L X42
Maximum allowable operating pressure	MPa	13.1
Date of commissioning	Year	1990
Young's modulus, E	GPa	210.7
Poisson's ratio, v	-	0.3
Yield strength, σ_y	MPa	290
Tensile Strength, σ_u	Mpa	495

Table 2. Properties of the composite materials [21]

Parameter	Unit	Infill	Composite wrap A
Young's modulus, E	GPa	19	14.34 (hoop) 10.1 (axial) 5.5 (radial)
Poisson's ratio, v	-	0.35	-
Tensile Strength, σ_u	MPa	20.01	241.27 (hoop) 169.43 (axial)
Density	kg/m^3	-	1659.2

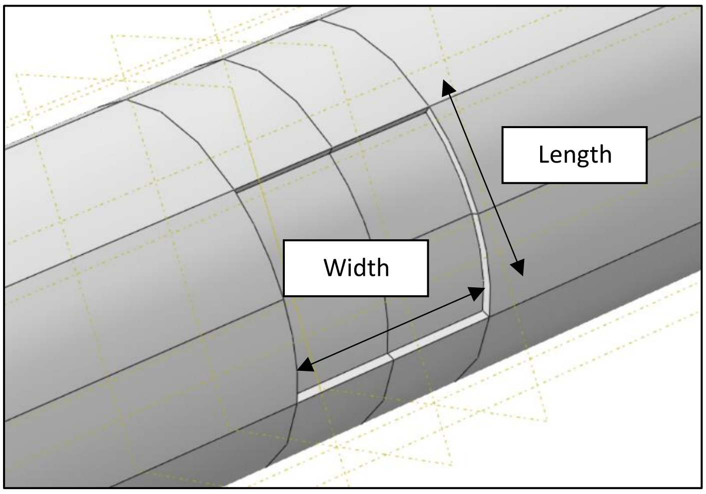

Fig. 4. Defect square shape of the corroded area

2.3. Finite element modeling (FEM) of defected and repaired with CFRP pipelines

In this section, a detailed FEM is constructed based on the criteria of the defected and repaired pipelines from the input data. The objective is to explore the influence of interactions various geometric factors to CFRP repair method. Four assumptions were implied during the FEM construction. First, the impact of the liquid contained in the pipeline during the operation was not taken into account, as suggested by Liu *et al*. [27]. Second, the thermal stress produced during the transportation of high-temperature media was not considered when designing the pipeline. Third, the connection between the body pipelines and repaired materials is assumed in perfect bonding where no other imperfect defect occurs like crevice corrosion. Last assumption is the working load practically exert the greatest effect on the pipeline which is the burst pressure. Thus, the burst pressure was assumed as the only factor that affects the pipeline study.

Referring to the recent study by Leong *et al*. [21], the research simulated the pipeline structure model using the ABAQUS Finite Element modeling software version 6.14 (Dassault Systemes Simulia, USA) to create the models, meshes, and perform the FE analysis. A corroded steel pipe, grout (putty), and composite wrap were used as the base model for this study, as illustrated in **Fig. 5**. A hollow steel pipe with a length of 1200 mm was constructed with an outer diameter, D of 168 mm and a wall thickness, t of 9.5 mm. A metal loss as defect measured in rectangular shape was modelled in the middle of the pipe. The grout was modelled to fill the defect area, while the composite wrap A was constructed as a thin shell layer with a diameter of 168 mm at a minimum length which is determined using Equation 1 [28], as follows:

$$L = 2L_{over} + L_{defect} + 2L_{taper}\, , L_{over} = 2\sqrt{Dt} \qquad \text{(Eq. 1)}$$

According to Equation 1, L_{over} is the axial thickness extent of repair and L_{defect} is the axial length of the defect. The L_{taper} was assumed to cover a length to repair thickness ratio of approximately 5:1 due to the axial loads caused by the burst pressure end effects, such as bending or thermal expansion. Then, individual components were assigned with relevant material properties based on the study by Lim et al. [5]. After assembling the component into an integrated structure for the analysis, the interaction between the various materials was created and the boundary conditions were applied. The optimal meshing size was generated on the structure before the analysis was performed on the pipeline's internal wall for 600 seconds at 60 MPa, which corresponds to a pressure rate of 0.1 MPa per second. The results of the pilot simulated FE model was compared to the previously published experimental test data. To consider the base model is validated, the error margin between the results should be less than 10% [29].

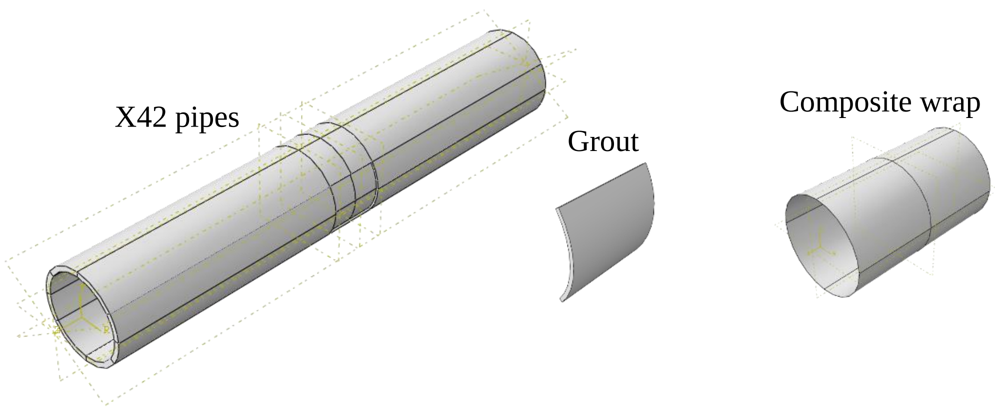

Fig. 5. Base modeling of the FEM consisting of the main hollow type X42 steel pipe, grout (putty), and the composite wrap A

2.4. Designation of ANN modeling

The ANN modeling was divided into few stages. In the first stage, selection of ANN parameters and pattern recognition tool were performed. The next stage involved the input data, designation of the ANN architecture process, hidden neuron setup, training process and model validation. The input data contains three different parameters comprising length(L), width(w), and depth(t). While, the output contains two parameters, the residual burst pressure that represent the unrepaired and repaired pipelines. It was crucial to acquire a broad range of data to produce the best ANN of the modeled study. The insignificant input variables would affect the network size, reduces model interpretability, slow down the learning process, and consequently leads to misconverge [30], [31]. Lastly, by using the trial error method, the ANN net is employed to train, validate, and testing the data to achieve the optimum ANN which produce the best results based on the parameters listed in **Table 3.**

Table 3. ANN design parameters

Parameter	**Details**			
Network	Feedforward network			
Number of layer and neurons	1st layer = 5 neurons 2nd layer = 5 neurons	1st layer = 8 neurons 2nd layer = 4 neurons		1st layer = 10 neurons 2nd layer = 2 neurons
Training function	Levenberg-Marquardt BFGS Quasi-Newton Conjugate Gradient with Powell/Beale Restarts			
Activation function	First and second layer			
	Purelin	Tansig	Logsig	Poslin
Data division	Random			
Normalization	Average method			
Performance	Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)			
Data distribution	Training = 80% Validation = 10% Testing = 10%	Training = 70% Validation = 20% Testing = 10%		Training = 60% Validation = 20% Testing = 20%

The data collected in the first stage was divided into three parts for training, validation, and testing. Splitting the data is important to ensure that the models are not trained and validated using the same data [31]. Given that the model could not be proven successful until it was validated. Therefore, a different portion of the data was used for validation purposes. Two mathematical equations, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), were used to see the fitness of the ANN models as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} (C_i - E_i)^2 / n} \qquad \text{(Eq. 2)}$$

$$MAE = \frac{\sum_{i=1}^{n} |C_i - E_i|}{n} \qquad \text{(Eq. 3)}$$

where E_i is the estimated value, n is the number of events, and C_i is the actual value. Both equations indicated that the model was sound and efficient when its value was close to zero and vice versa. The framework of the model is shown in **Fig. 6**. The ANN uses algorithms to train the data by learning and adapting until the objectives were met. The optimization coding was set so that the optimum model was generated in several series of cycles.

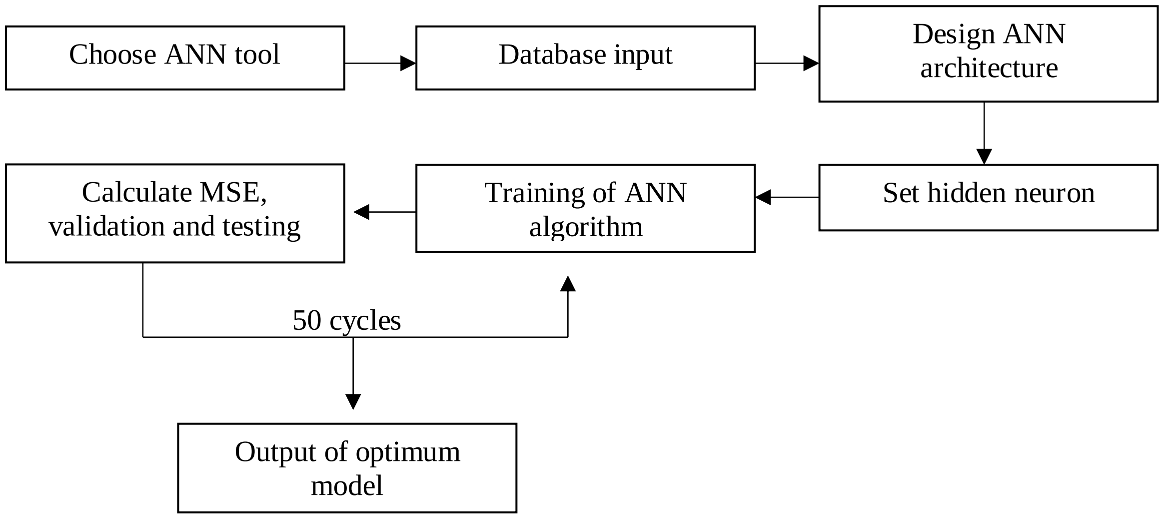

Fig. 6. Framework of the ANN model

3. Discussion

3.1. Validation of pilot FE modeling

Before the FE modeling can be used to analyze the input data, the models must first be validated to ensure a reliable output. A pilot model was developed based on the samples studied by Oh *et al*. [22] for unrepaired pipes and Lim *et al*. [5] for repaired pipes. **Fig. 7** shows the tested pipe sample X65 used by Oh *et al*. [22] and X42 used by Lim *et al*. [5], both for underwater purposes. Both laboratory tests were used to develop and analyse the pilot FE under burst pressure conditions with both ends set in a rigid-close boundary state. The size of the defect area was 200 mm x 200 mm with 50% artificial corrosion metal loss. The validation of burst pressure showed error differences for unrepaired and repaired are 4.32% and 7.39%, respectively. The FE stress pattern also showed similarity with the findings in both sample testing. Therefore, the pilot FE model was validated for use in this study.

Fig. 7. Pipelines burst pressure test based on past studies by (left) [22] and (right) [5]for the validation of the pilot FE model

3.2. Numerical analysis

The failure of the pipeline model was determined by examining the changing burst pressure trend of the pipeline material. When the tension stress in the body pipeline or composite section exceeds the ultimate tensile stress, the materials reached its failure point because of the load-bearing capacity is less than the ultimate stress that the materials can tolerate. This region of high-stress concentration, as predicted via the FE analysis, was regarded as the pipe's failure point. The stress experienced by FE models for each element with an 80% corrosion level is shown in **Table 4**. Based on the results, the bare pipe and the putty reached the ultimate stress at 506.2 MPa and 20.01 MPa. Value of stress for the repaired composite, for models 3 and 4 decrease compared to model 2. This concluded as the defect size became smaller, the composite experienced greater stress due to the high pressure per area that occurred at the defected region.

Table 4. Stress of unrepaired and repaired materials with an 80% corrosion level

Model no.	Corrosion level (%)	Defect size (mm x mm)	Burst pressure (MPa)		Maximum tensile stress (MPa)		
			Unrepaired	Repaired	Repaired		
					Pipe	Putty	Composite
2	80	200 x 200	14.1367	21.8193	506.2	20.01	353.7
3		100 x 100	22.1280	24.1699	506.2		204.2
4		75 x 75	29.2216	29.0395	506.2		207.8
5		50 x 50	41.0948	32.2699	437.5		221.0

Fig. 8. Burst pressure of repaired and unrepaired corroded pipelines with different corrosion severity and defect area

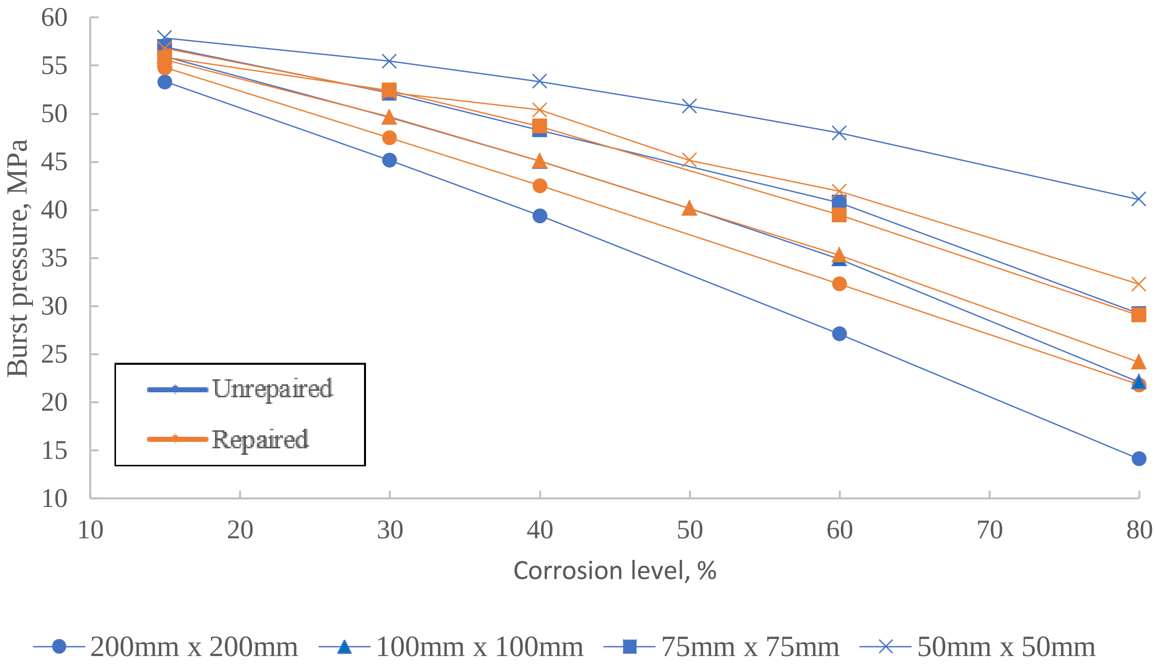

Fig. 8 depicts the burst pressure for different defect shapes and corrosion levels. According to the findings, the effect of composite repair for 200 mm x 200 mm defect size demonstrated an increase of burst pressure between 2% and 19% at corrosion levels of 15% to 60%, and 54% at corrosion levels of 80%. The results indicate strong effectiveness of composite repair at 37% of the pipe diameter surface ratio to defect size. Interestingly, the finding are consistent with those of past studies by Zhang *et al*. [32] and Leong *et al*. [21], which found that a larger defect area on corroded pipe led to a lower pressure required to cause a leak or rupture. For the 100 mm and 75 mm defect sizes, the burst pressure between the repair and unrepaired pipe are almost identical. Contrast to the 50 mm defect size, a deterioration of 2% to 21% burst pressure was recorded at corrosion level of 15% to 80%. This concludes the ineffectiveness of the composite repair to restore the integrity of the pipes from failure for the 50 mm defect size.

3.3. Composite analysis

The main objectives of this study is to determine the assessment of composite wrap as the repair material at the corroded area. **Fig. 9** illustrates the stress of the failure composite wrap, where the red area denotes the highest stress that occurred on the material's surface. For the 50 mm size defect with a corrosion level of 80%, the highest stress was concentrated at the centre edge of the defect area, as shown in **Fig. 9(a)**. This was contrary for the 15% corrosion level in which the maximum stress was concentrated at the centre covering almost 80% of the defect area. As for the infill material, the critical stress was observed to occur in line with the stress from the main pipe's body. In addition, both models recorded a lower value of burst pressure compared to the unrepaired models, indicating that the repaired material failed before the main body breakdown. When the defect size increased, the stress of the main pipes dispersed uniformly throughout the defected area, as presented in **Fig. 9(b)**. The same pattern of stress also shown by the composite wrap and putty materials, where these models recorded the highest increase of burst pressure than the unrepaired pipes. Hence, the functionality of the repaired material was proven via the FE analysis.

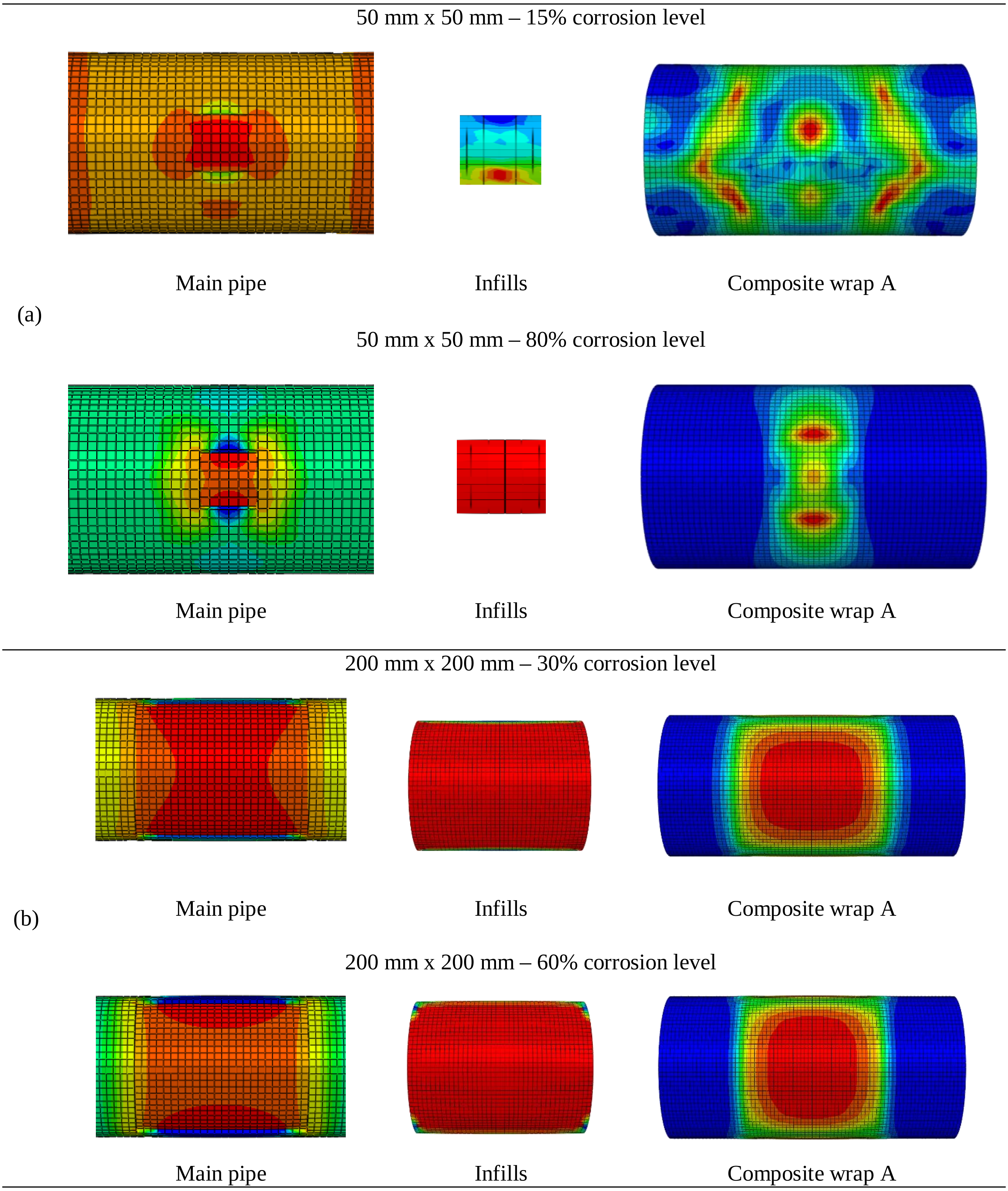

Fig. 9. Stress behaviour of the FE models with defect size of (a) 50 mm x 50 mm and (b) 200 mm x 200 mm

3.4. Performance of the ANN analysis

The model prediction and reliability performance are based on probability and validation accuracy. Uncertainties are unavoidable when dealing with real-world (data) situations [33]. Therefore, the ANN models were developed with different design parameters until the output percentage difference with the FE output data are less than 5%. Out of the 50 trials and errors conducted for the ANN models using the design parameters in **Table 3**, Model ANN no.25 is the best model with the lowest RMSE and MAE values of 0.0024 and 0.004. The output data of Model ANN no.25 burst pressure for unrepaired and repaired pipes is shown in **Fig. 10** where clearly shown an error of less than 5% for all ANN data compared to the FE data.

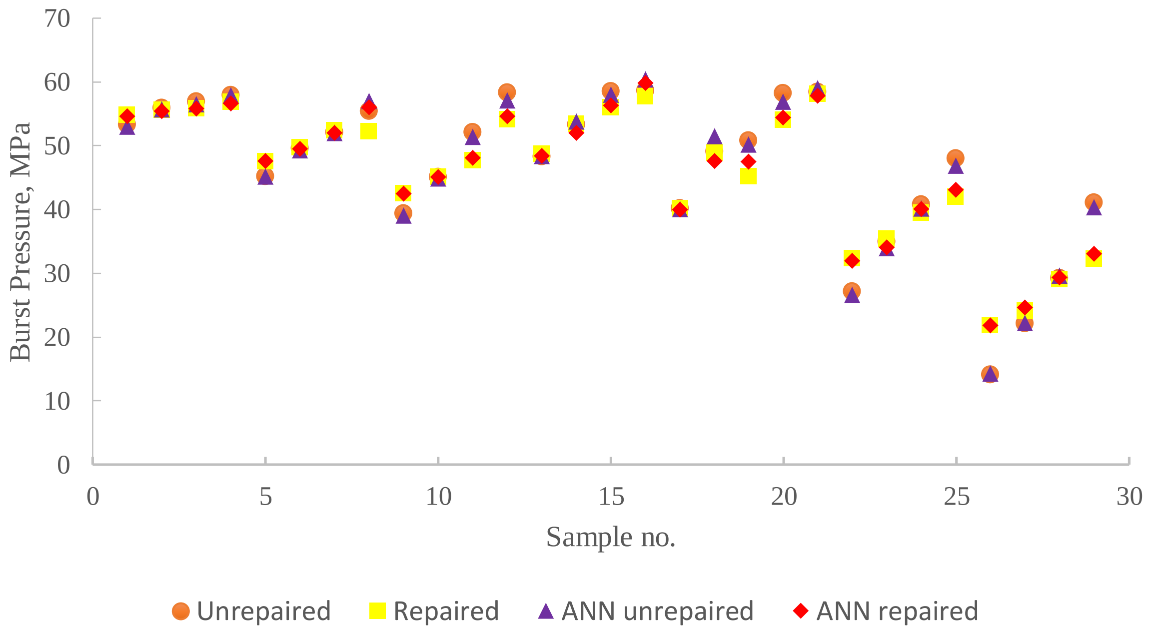

Fig. 10 Burst pressure of the Model ANN no. 25

Nevertheless, Models ANN No.25 performance needs to be evaluated with real-case data to verify the soundness of the ANN model. Historical data contains more generic and complicated data, the defect properties also are diverse in small intermittent constituents. Therefore, an analysis was conducted between the output data from the model No.25 and the FE from the historical inspection data, as presented in **Table 5** and **Fig. 11**.

Table 5. Burst pressure analysis for unrepaired pipes

Location (m)	Defect position (H:M)*	Depth (%)	Length (mm)	Width (mm)	Unrepaired pipes		Error (%)
					FE	ANN	
1420.38	9:54	50	15	51	57.6335	56.4106	2.12
1717.77	12:36	49	12	59	57.9347	58.4517	0.89
32.51	12:04	41	23	51	57.2455	57.1631	0.14
1492.45	3:14	41	13	15	58.3059	57.4469	1.47

*H:M = (Hour:Minute)

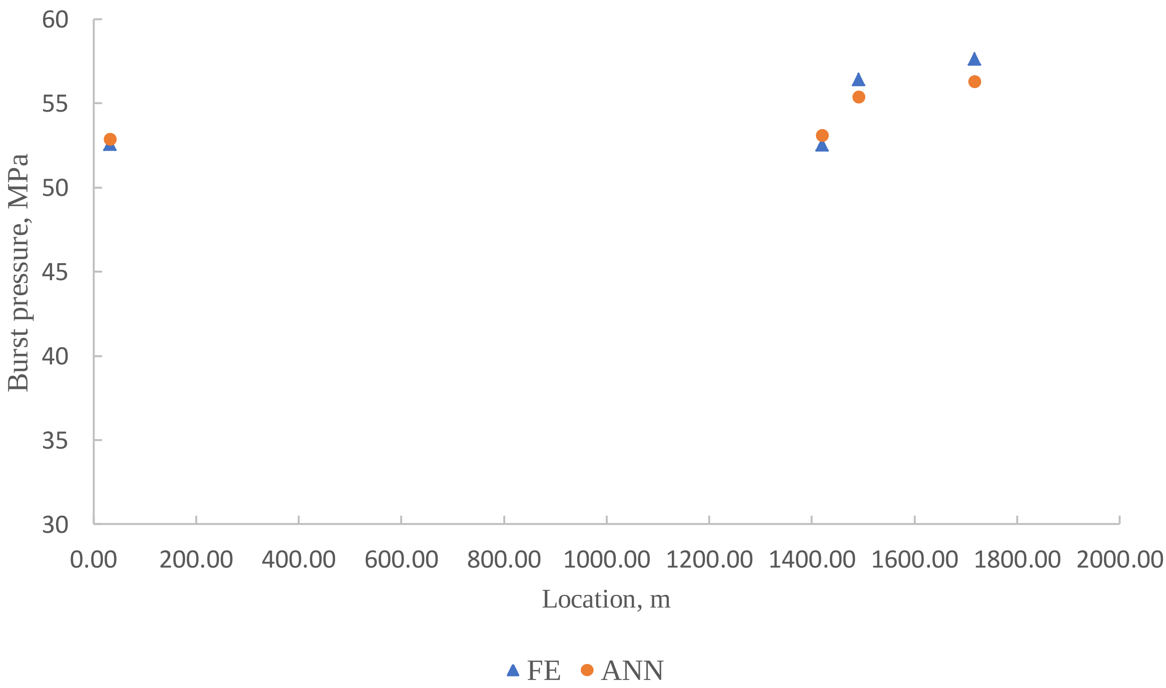

Fig. 11. Burst pressure comparison for repaired pipes

It appears from **Table 5** that the error between the FE and the output from ANN model No.25 for unrepaired pipes is below than 5%. The comparison graph of burst pressure for repaired pipes in **Fig. 11** shown similarity with a margin error of less than 3%. The findings proved that the designed ANN model was able to predict the rehabilitate pipe's strength with high precision. As the objective of this study was to predict the strength of composite repaired and its suitability. The results demonstrated that in certain defect size, the burst pressure of repaired pipes was significantly less than the unrepaired pipes where it's indicated that the composite repaired failed first under the applied stress before steel pipes breaks off.

4. Limitation

The efficiency of the ANN model was highly dependent on the data input employed in this study. Each FE model required approximately 48–72 hours to analyse its behaviour. Due to the limited range of data input, the constructed models were only accountable for the type X42 steel pipes and repair materials, which was specifically studied in this research only and may not be replicated using other types of pipes under different conditions.

5. Conclusions

This study was carried out to design an ANN model with the ability to predict the burst pressure of composite repaired subsea pipelines and evaluate the suitability assessment of CFRP. The research findings provided new insights on the development of repaired composite for subsea pipelines and pre-information on repaired assessment, which would conveniently assist engineers to plan and adapt effective rehabilitation methods. Among the significant conclusions that can be drawn from this work include:

1. The composite repaired material study was ineffective when the predicted burst pressure decreased after the repaired analysis was performed.
2. CFRP A repaired method was effective for defect size greater than 50 mm x 50 mm at any level of corrosion.
3. The constructed ANN models were able to predict the burst pressure of the corroded and repaired subsea pipelines using CFRP A with an error below 5%.

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