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Application of Particle Swam Optimization (PSO) in Oil and Gas Pipeline under Spatially Varying Corrosion Defects

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Abstract: This paper proposes the application of particle swarm optimization (PSO) technique to oil and gas pipeline under spatially varying corrosion defects. The PSO results show that to keep the oil flowing in the pipe and still minimize the corrosion rate the pipeline system should be at its optimum performance values, that is, the optimum corrosion rate obtained from the PSO is 0.0277mm/year and this is achievable at optimum water cut of 11.41%, temperature of 30.75^{0}C, pH value of 5.66, pipe age not more than 10years, fluid flow velocity of 2.69m/s, partial pressure of CO_2 at 0.2MPa and hydrogen sulphide concentration not more than 0.1mol/L. The PSO results also show that higher temperatures and age of pipe will drastically increase the corrosion rate. From the PSO results, it is clear that the pipe thickness will be reduced by a maximum of 0.277mm and a minimum of 0.1579mm after 10 to 50years of continuous operation.
Keywords: particle swarm optimization (PSO), pipeline

INTRODUCTION

Optimization is a mathematical technique used to find maxima or minima of functions in some feasible region and a variety of this technique compete for the best solutions. Particle Swarm Optimization (PSO) is a relatively new method of optimization that has been empirically shown to perform well on many of such problems [1] finding the global optimum solution in a complex search space. The Particle Swarm Optimization algorithm is a novel population-based stochastic search algorithm and an alternative solution to the complex non-linear optimization problem. Inspired by the social behavior of birds, it was studied by Craig Reynolds (a biologist) in late 80s and early 90s. He derived a formula for representing the flocking behavior of birds. This was later used in computer simulations of virtual birds, known as Boids, recognized the suitability of this technique for optimization in 1995 and its basic idea was originally inspired by simulation of the social behavior of animals such as bird flocking, fish schooling and so on [2].

Corrosion Process

The term corrosion is the wearing off of metal materials starting from the surface. The process involves metal surface breakdown and subsequent removal of the weak materials and it is one of the major causes of pipeline failure in oil and gas industries [3]. The process of material breakdown in corrosion is an electrochemical process [4]. In pipes corrosion process occur in both internal and external pipe surfaces. The internal corrosion is usually influenced by properties of fluid flowing in the pipe, while the external corrosion occurs as result of the influence of the properties of the pipeline surroundings [5]. The internal corrosion of pipes used to transport oil and gas are influenced by physical and chemical properties of the transported oil or gas. These properties are the temperature, operational pressure, flow rate, pH, water content, CO_2 and O_2 content and dissolved solids [6].In oil and gas pipelines, the major cause of internal corrosion is CO_2 because it is injected into the pipelines to enable quick oil recovery [6]. In CO_2 corrosion electrochemical process, iron is dissolved in the anode and hydrogen is evolved in the cathode according to the following chemical equation [7].

$$F_e + C0_2 + H_2 0 \rightarrow F_e + C0_3 + H_2 \qquad (3.1)$$

$FeCO_3$ is a scale on the steel surface called rust. At higher temperatures, the scale, Fe_3O_4 is formed. Both scales can be protective or non-protective depending on the conditions of their formation.

H_2S and O_2 also cause corrosion in the internal wall of oil and gas pipelines [6]. These corrosion processes also result in the formation of weak scales inside the pipes. The chemical equations representing H_2S and O_2 corrosion processes respectively are as follows [8].

$$F_e + H_2S \rightarrow F_eS\,H_2 \quad (3.2)$$

$$3F_e + O_2 + 4H_2O \rightarrow 3F_e\,(OH)_2\;\;H_2 \quad (3.3)$$

In all the cases, the anodic and cathodic reactions are represented by the following chemical equations respectively [2,9]

$$F_e \rightarrow F_e^2 + 2\bar{e} \quad (3.4)$$

$$2H + 2\bar{e} \rightarrow H_2 \quad (3.5)$$

The equations explain the oxidation and reduction reaction that take place at the anode and cathode respectively. The anode is the metal surface where the charges (electrons are removed from metal into solution, and the cathode is the surface where the metal electrons are introduced into the metal. From the chemical equations, it is clear that the presence of CO_2, H_2S, O_2 and water causes the internal corrosion of pipes carrying oil/gas; therefore, it isimportant that these four parameters should be included in corrosion modelling of oil and gas pipelines for better results [10]. All the fluid properties that influence these chemical reactions will have effect on the corrosion rate of the pipelines. It can also be inferred that the corrosion rate of internal wall of oil and gas pipelines is proportional to the rates of the above chemical reactions. Corrosion of metal surface have been explained by electrochemical theory and confirmed experimentally by many authors. The theory explained that metal surface in contact with corrosion-promoting solution has several sections with different electrical potential levels. These result in the formation of local short circuits which cause corrosion on the surface of the metal [5].The whole process gradually leads to corrosion pit initiation which then grows continuously with time and the risk of pipeline failure. Fig.1 shows the propagation of localised corrosion on the inner surface of steel pipes for oil/gas transportation.

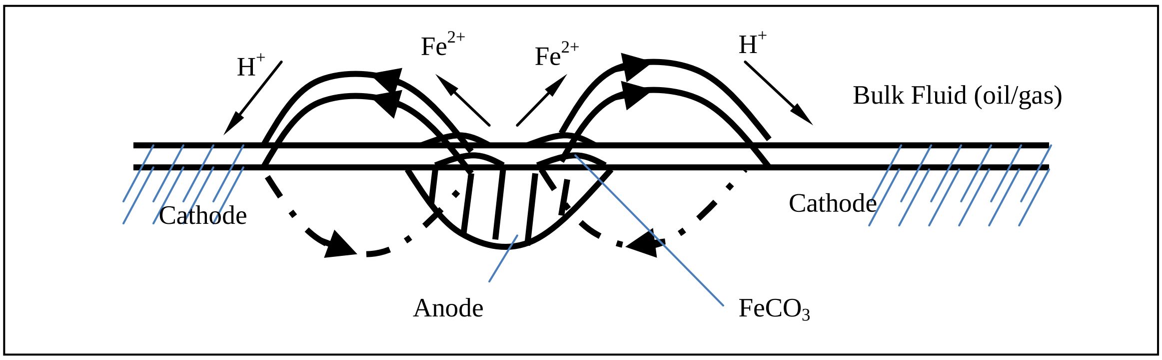

Fig-1: Localized corrosion of steel surface [5]

The Power Model

The maximum pit depth of corroded low carbon steel has been modelled using power law. Both internal and external corrosion depths are related to exposure times by an equation which takes the form given in (3.6) [12]

$$d = cT^v \quad (3.6)$$

where d = pit depth [mm]

T = exposure time [years]

C = pitting proportionality factor [mm/year^v]

V = exponent proportionality factor

Equation (3.6) is used to predict the maximum pit depth [5], C and v being constants v is assumed to have a value ranging from 0.3 to 1.0 and C is taken to be approximately 2.0 from the work of Lee in 2011 . This equation was originally developed by Romanoff to predict the external corrosion of pipes buried in soil [5] and later, extended to take into account the time of pit initiation [11] giving rise to equation (3.7)

$$d = c\left(T - T_o\right)^v \qquad (3.7)$$

where T_o = pit initiation time (years)

Velázquez and his co-researcher use this equation to model the pit depth and pitting rate of external corrosion of buried pipelines. Using a multivariate non-linear regression analysis, they concluded that the pitting proportionality and the exponential factors can be determined from the soil properties and soil/pipe potentials [12].

Two-Phase Model

The two phase model was developed to determine the corrosion pit depth and pitting rate of steel and iron. According to the proposal made by [11] the two phase model takes the form below;

$$d = aT + b\left(1 - e^{-kT}\right) \qquad (3.8)$$

$$d_T = a + bce^{-kT} \qquad (3.9)$$

Where d = corrosion pit depth (mm)

d_T = Corrosion pitting rate (mm/year)

T = Exposure time (years)

a = Final pitting rate constant (= 0.009mm/year)

b = Pit depth scaling constant (= 6.27mm)

k = Corrosion rate inhibitor factor (= 0.14year^{-1})

This model is barely used in recent research interests for corrosion modelling. The model development procedure is shown in the diagram below.

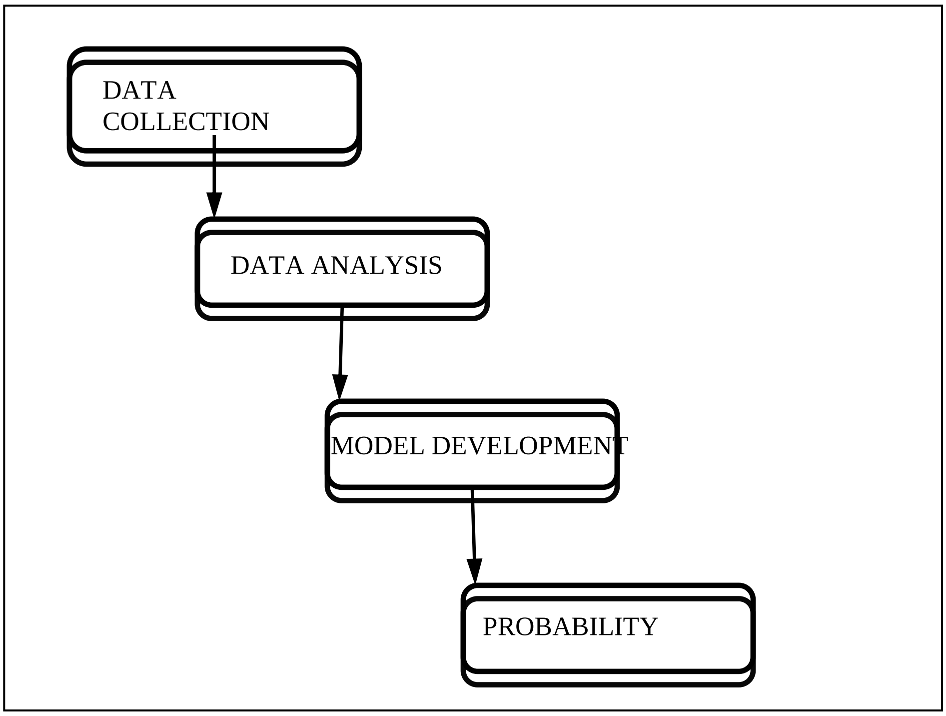

Fig-2: Proposed model development stages

Table-1: Model Variables

S/N	PARAMETER	UNIT	TYPE OF VARIABLE
1	Temperature	^oC	Predictor
2	Partial Pressure of CO_2	MPa	Predictor
3	Hydrogen Sulphide Concentration	mol/L	Predictor
4	pH	-	Predictor
5	Flow rate	m/s	Predictor
6	Water content	%	Predictor
7	Pipe Diameter	mm	Predictor
8	Pipe length	m	Predictor
9	Age of pipeline (exposure time)	year	Predictor
10	Corrosion rate	mm/year	Predicted
11	Defect Depth	mm	Predicted

Data Analysis

Data collected were first subjected to statistical and spatial analysis. These analyses are necessary to identify the best model for oil and gas pipelines corrosion in Niger Delta. The diagram below shows the data analysis types taken in this work.

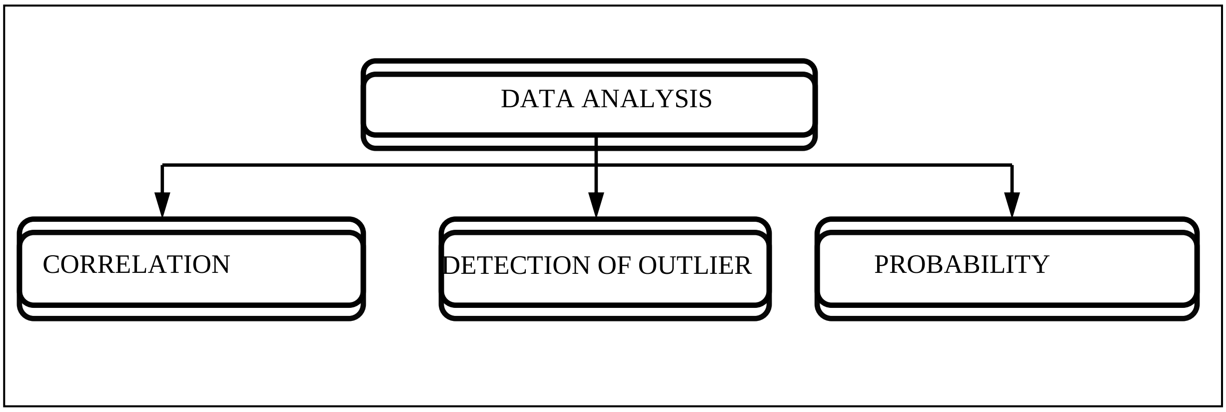

Fig-3: Data analysis type

Model Formulation

There are foundational models which many researchers have built on to develop theirs for particular situations based on their study scopes. The analysis of the field data collected for this work shows that linear model will be statistically incorrect for this work. Also power model have been shown to yield better results by many investigators Therefore power model was chosen as a foundation for the proposed model development in this work.

Basic Assumptions

For appropriate predictive model to be made, the following assumptions were made:

- There is a time difference called pit initiation time between corrosion pit depth (defect depth) formation on the pipelines and the time of installation.
- The corrosion rate is equal to the corrosion pit growth rate in (mm/year)
- The corrosion pit growth obeys the power law
- The corrosion inhibitors used in the pipelines under consideration reduce the corrosion rate by some factor k.
- The corrosion process was initiated and propagated by the influence of the predictor parameters considered in this work.

Proposed Regression Model

The pit depth of internally corroded pipeline was proposed to obey the formula;

$$p_d = c(t - t_o)^\eta \quad (3.12)$$

Where t = pipeline age (years)

t_o = corrosion initiation time [years]

C and η are proportionality and exponent parameters respectively.

Assuming that the corrosion rate is minimised by some inhibitors by a factor k, then equation (3,12)becomes;

$$p_d = kc(t-t_o)^{\eta} \quad (3.13)$$

Thus, the proportionality parameter becomes

$$\rho = kc \quad (3.14)$$

And

$$p_d = \rho(t-t_o)^{\eta} \quad (3.15)$$

The proportionality and exponent parameters are modelled to depend on the fluid parameters as follows;

$$[c,\eta] = f\ (T, P_c, P_h, W, H, V) \quad (3.16)$$

Where $c_i, i = 0,1,...,6 =$ constants

$T =$ Mean temperature of oil (^{0}C)

$P_c =$ Partial pressure of CO_2 (MPa)

$P_h =$ pH of oil (-)

$W =$ Water content of oil (%)

$H_c =$ Hydrogen Sulphide Concentration (mol/L)

$V =$ Oil flow rate (m/s)

Corrosion rate is taken to be the rate of change of pit growth with time; therefore, the corrosion model was developed by taken time derivative of the defect depth as shown;

$$CR = \frac{d(Pd)}{dt} \quad (3.17)$$

$$CR = k\eta c(t - t_o)^{\eta-1} \quad (3.18a)$$

$$CR = \eta p(t - t_o)^{\eta-1} \quad (3.18b)$$

Particle Swam Optimization (Pso) Model

Numerous problem encounters in real life situation cannot be solved by one objective function hence;an optimization problem may have more than one objective. The objectives of the problem normally conflict. Therefore, the best compromises between the given objectives generate a set of solutions to the given problem PSO have the following advantages [14].

- PSO algorithm is a derivative-free algorithm.
- It is easy to implement, so it can be applied both in scientific research and engineering problems.
- It has a limited number of parameters and the impact of parameters to the solutions is small compared to other optimization techniques.
- The calculation in PSO algorithm is very simple.

- There are some techniques which ensure convergence and the optimum value of the problem calculates easily within a short time.
- PSO is less dependent of a set of initial points than other optimization techniques.
- It is conceptually very simple.

Pso Algorithm Parameters

PSO parameters determine how efficient the algorithm will be in its performance. Some of these parameters have large impact on PSO performance while others do not [13].

PSO PROBLEM FORMULATION AND SOLUTION PROCEDURES

An objective function is required for every optimization problem. The function to be optimized in this work is the corrosion pit depth and the corrosion rate model given in equation (3.15 and 3.18b). The aim is to determine the optimum value of each of the predictor parameters that will minimize the corrosion pit depth and corrosion rate. Thus, this is a minimization problem.

$$P_d = \rho(t - t_o)^{\eta} \quad (3.15)$$

$$CR = \eta\rho\,(t - t_o)^{\eta-1} \quad (3.18b)$$

Where;

$$\rho = kc \quad (3.14)$$

$$\eta = f\left[most\ \mathrm{inf}\ luencial\ of\ \left(T, P_c, P_h, W, H_c, V\right)\right] \quad (3.19)$$

$$c = f\left[most\ \mathrm{inf}\ luencial\ of\ \left(T, P_c, P_h, W, H_c, V\right)\right] \quad (3.20)$$

This minimization problem is subjected to the following constraints;

$$t + sum\ (\eta \cup c) \leq sum\ [\max(\eta \cup c\ \ data\ value)] \quad (3.36)$$

$$t + sum\ (\eta \cup c) \leq sum\ [\min(\eta \cup c\ \ data\ value)] \quad (3.37)$$

Upper bound = $[\max\ (\eta \cup c\ \ data\,value)]$ (3.38)

Lower bound = $[\min(\eta \cup c\ \ data\,value)]$ (3.39)

The following PSO parameters were adopted in this work [14]

Table-4: PSO Parameters

Parameter	Symbol	Value
Inertial weight:	W1, w2	0.9, 0.4
Acceleration factors	C1 c2	2.05, 2.05
Population size:	N	100
Maximum iteration	Mit	1000
Initial velocity	$v_{i,o}$	10 % of position
Maximum Number of run	Run	10

The flow chart in Fig 6 shows the PSO algorithm used in this work. PSO tool in MATLAB 2014b was used to carry out the analysis.

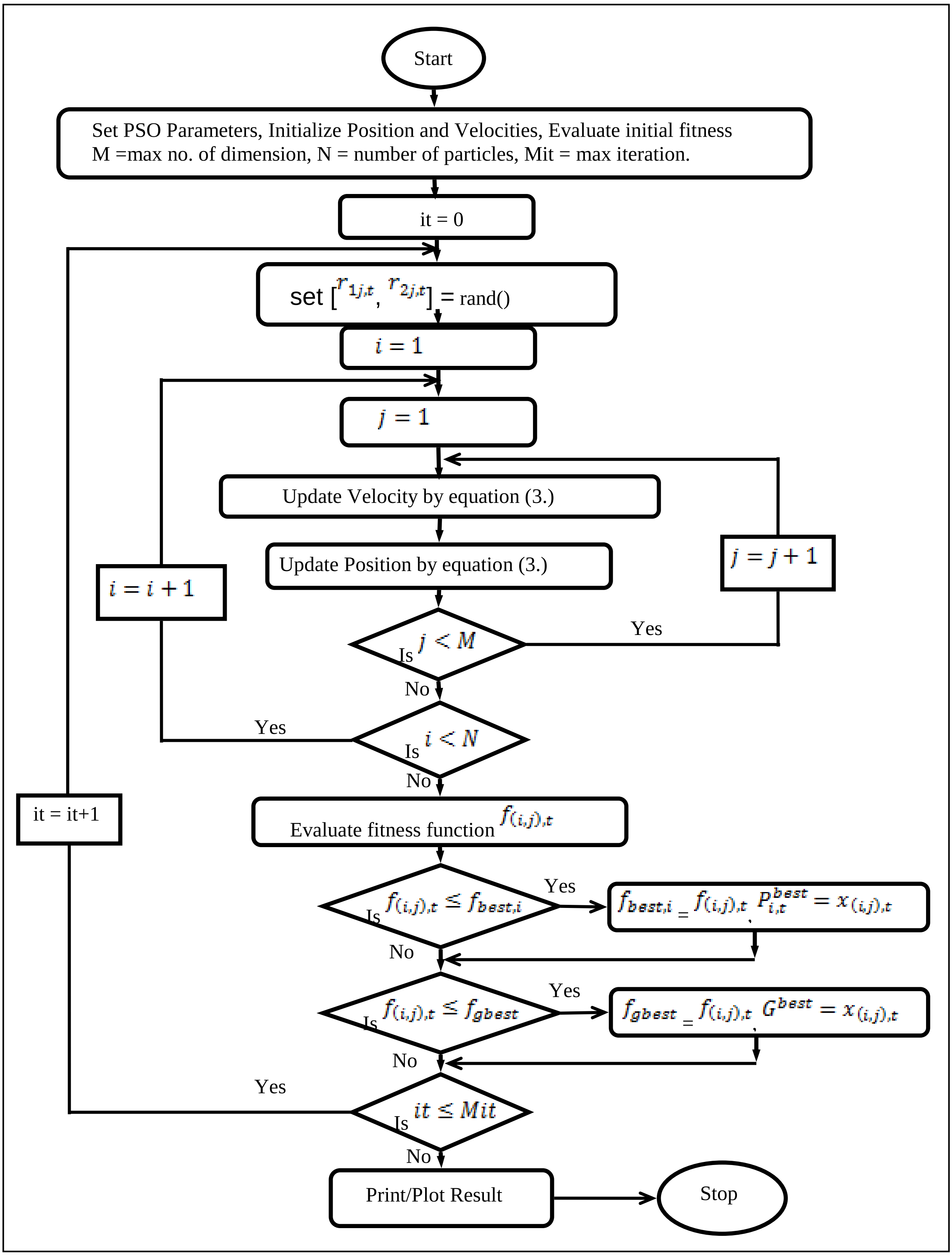

Fig-6: Flow Chart for PSO Algorithm

RESULTS AND DISCUSSION

This chapter contains the results of the models developed in chapter three. Model analysis and validation were discussed here

Result of Regression Analysis

To find out which of the predictor parameters influence the values of c and η, multiple regression analysis was carried out for 4096 different combinations of the six predictor parameters between c and η. The best five combinations and their corresponding correlation coefficient are tabulated below.

Table-4.1: Best five models for C and η

S/N	Relationship for Proportionality Parameter (c)	Relationship for Exponent Parameter (η)	R^2
1	$c = c_o + c_1 V + c_2 P_c$	$\eta\ n_o + n_1 V + n_2 P_C + n_3 P_h + n_4 H_C$	0.634
2	$c = c_o + c_1 V + c_2 P_c + c_3 H_c + c_4 P_h$	$\eta = n_o + n_1 V + n_2 P_C$	0.688
3	$c = c_o + c_2 P_c + c_3 H_c$	$\eta = n_o + n_1 V + n_2 P_C + n_3 H_C + c_1 V$	0.705
4	$c = c_o + c_1 V_c + c_2 P_c / P_h$	$\eta = n_o + n_1 V + n_2 P_C + n_3 H_C$	0.764
5	$c = c_o + c_1 W_c + c_2 T + c_3 P_h$	$\eta = n_o + n_1 V + n_2 P_C + n_3 H_C$	0.803

The MATLAB print out of the best result statistics after all outliers have been removed is shown that, This result was obtained at $t_0 = 0.5$ years (6 months). The final result has 0.821 the value of R^2 and the following relationships.

$$\eta = n_o + n_1 V + n_2 P_C + n_3 H_C \qquad (4.1)$$

$$C = C_o + C_1 W + C_2 T + C_3 P_h \qquad (4.2)$$

$$\rho = k\left(C_o + C_1 W + C_2 T + C_3 P_h\right) \qquad (4.3)$$

$$CR = \eta\rho(t - 0.5)^{\eta-1} \qquad (4.4)$$

$$P_d = \rho(t - t_o)^{\eta} \qquad (4.5)$$

Table-4.2: Estimated Coefficients:

S/N	Constant	Estimate	SE	t-Stat	p-Value
1	K	0.0134960	0.00041855	1.9367	0.056882
2	c_1	-0.0038423	0.0045095	-0.85205	0.39718
3	c_2	0.0053544	0.0027261	1.9641	0.053605
4	c_3	-0.028141	0.01977	-1.4234	0.15919
5	n_1	0.035424	0.016453	2.1531	0.034864
6	n_2	0.35929	0.099313	3.6177	0.00056632
7	n_3	0.36053	0.18434	1.9558	0.054597
8	c_o	0.49896	0.23719	2.1036	0.039117
9	n_o	1.3728	0.11813	11.621	8.2389e-18

Number of observations: 77, Error degrees of freedom: 71
Root Mean Squared Error: 0.0211
R-Squared: 0.832
Adjusted R-Squared 0.815
F-statistic vs. constant model: 48.2
p-value = 6.37e-24

PARTICLE SWAM OPTIMIZATION (PSO) RESULT

The objective function optimized is the models in equations (4.4) and (4.5).

$$CR = \eta\rho(t-0.5)^{\eta-1} \qquad (4.4)$$

$$P_d = \rho(t-0.5)^{n} \qquad (4.5)$$

Where;

$$\eta = 1.3728 + 0.035424V + 0.35929P_c + 0.36053H_c \quad (4.6)$$

$$\rho = 0.006736 - 0.0000519W + 0.0000723T + 0.0003799P_h \quad (4.7a)$$

Minimize

$$1.3728 + 0.035424V + 0.35929P_c + 0.36053H_c \times 0.006736 - 0.0000519W + 0.0000723T + 0.0003799P_h$$

$$CR = (t-0.5)\left(^{1.3728 + 0.035424V + 0.35929P_c + 0.36053H_c}\right) - 1 \quad (4.7b)$$

From equation (4.5) corrosion pit depth $\left(P_d = \rho(t-0.5)^n\right)$
Where;

$$\eta = 1.3728 + 0.035424V + 0.35929P_c + 0.36053H_c$$

$$\rho = 0.006736 - 0.0000519W + 0.0000723T + 0.0003799P_h$$

$$P_d = \left(0.006736 - 0.0000519W + 0.0000723T + 0.0003799P_h\right) \times (t-0.5)^{\left(1.3728 + 0.035424V + 0.35929P_c + 0.36053H_c\right)} \quad (4.7c)$$

Constraints inequalities are derived based on field data;

$$49.2 \leq t + W + T + P_h + V + P_c + H_c \leq 160.1 \quad (4.8)$$

The inequality in equation (4.9) is divided into two as follows;

$$t + W + T + P_h + V + P_c + H_c \leq 160.1 \quad (4.9a)$$

$$t + W + T + P_h + V + P_c + H_c \geq 49.2 \quad (4.9b)$$

$$0.35 \leq P_C V \leq 0.64 \quad (4.10)$$

For equation (4.4) additional constraint stated in equation (4.11) below is required

$$25 \leq Vt \leq 32 \quad (4.11)$$

The upper and the lower bound of the predictor variables are also taken from the field data. They are given in table 4.6 as;

Table-4.6: Variables' upper and lower bounds

Parameter	Symbol	Unit	Upper Bound	Lower Bound
Water cut	w	%	30	5
Temperature	T	^{0}C	70	30
pH	P_h	-	6.5	4.0
Age of pipe	t	years	50	10
Flow speed	V	m/s	3.2	0.5
Partial Pressure of CO_2	P_c	MPa	0.7	0.2
H_2S concentrationconcentration	H_c	mol/L	0.3	0.1

These formed the input data for the PSO. The PSO output is given in table 4.7 - 4.10 Below.

Table-4.7: Best (Optimum) Parameters' Values for Corrosion pit depth

Parameter	Unit	Global best Value (Gbest)
Water cut	%	16.1878
Temperature	^0C	30.0000
pH	-	6.5000
Age of pipe	years	10.0000
Flow speed	m/s	3.2000
Partial Pressure of CO_2	MPa	0.2000
H_2S concentration	mol/L	0.1000

Table-4.8: Best PSO Parameters' Values for Corrosion pit depth

S/N	Best PSO Parameter	Value
1	Iteration	121 iterations
2	Elapse time	7.273224seconds
3	Best Practice	64
4	Best run	3
5	Best pit depth	0.1579mm

Table-4.9: Best (Optimum) Parameters' Values for Corrosion rate

Parameter	Unit	Global best Value (Gbest)
Water cut	%	11.4089
Temperature	^0C	30.7472
pH	-	5.6614
Age of pipe	years	10.0000
Flow speed	m/s	2.6851
Partial Pressure of CO_2	MPa	0.2000
H_2S concentration	mol/L	0.1000

Table-4.10: Best PSO Parameters' Values for Corrosion rate

S/N	Best PSO Parameter	Value
1	Iteration	37 iterations
2	Elapse time	7.571447seconds
3	Best Practice	25
4	Best run	6
6	Best Corrosion rate	0.0277mm/yr

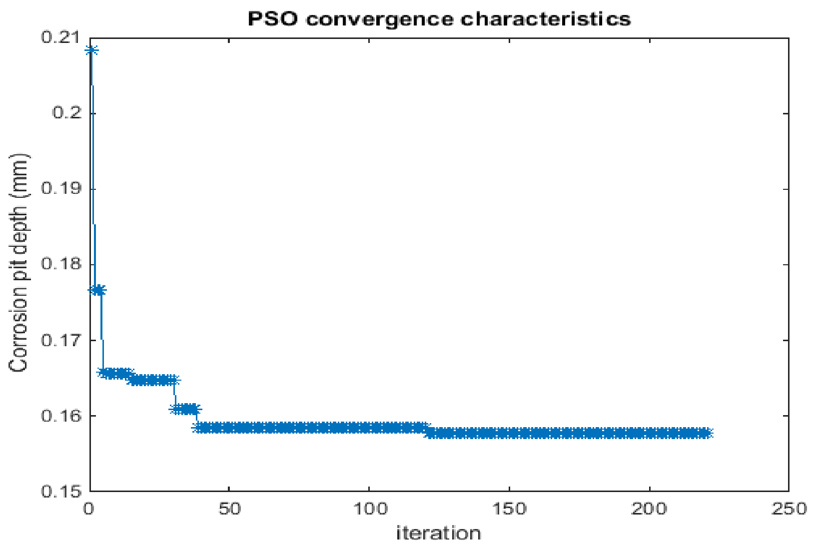

Fig-4.27: PSO convergence Characteristics for Corrosion pit depth

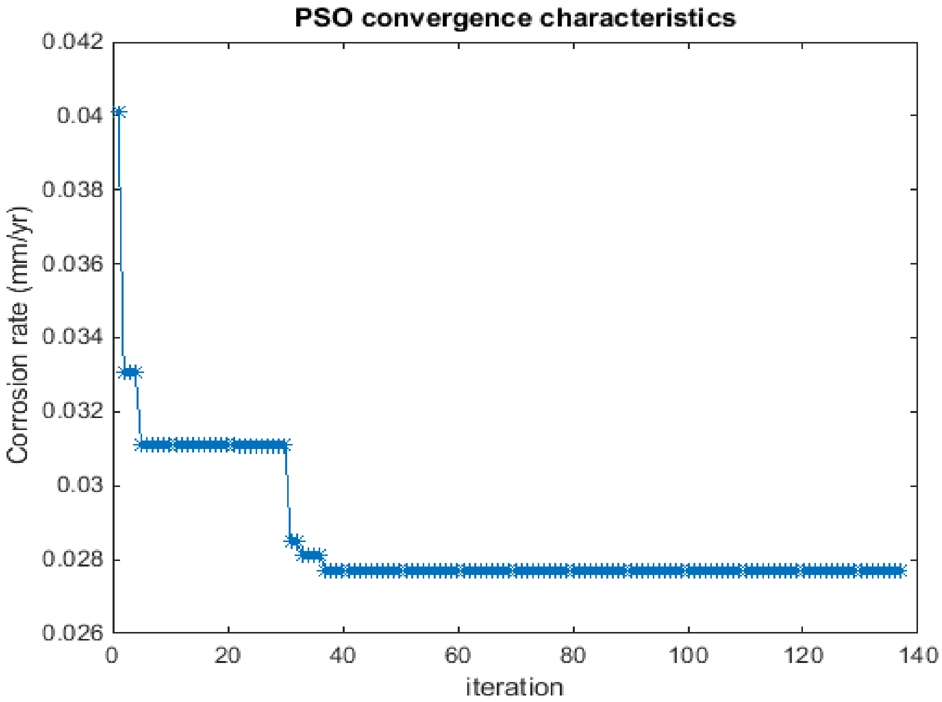

Fig-4.27: PSO convergence Characteristics for Corrosion rate

CONCLUSION

From the Result of PSO analysis performed on corrosion rate, the optimum corrosion rate is 0.0277mm/year and this corresponds to optimum parameter values which are; water cut = 11.41%, Temperature = 30.75^{0}C, pH value = 5.66, Pipe age = 10years, Fluid flow velocity = 2.69m/s, Partial pressure of CO_2 = 0.2MPa and Hydrogen Sulphide concentration = 0.1mol/L.

The PSO analysis of corrosion pit depth gives an optimum pit depth of 0.1579mm at optimum parameter values which are; water cut = 16.19%, Temperature = 30^{0}C, pH value = 6.5, Pipe age = 10years, Fluid flow velocity = 3.2m/s, Partial pressure of CO_2 = 0.2MPa and Hydrogen Sulphide concentration = 0.1mol/L.

From both results, it can be deduced that, for minimum corrosion rate and hence chances of failure, the water cut should be in the range of 11.41% to16.19%, Temperature should a bit above room temperature, pH should be in the range of 5.7 to 6.5, the pipe lines should be in operation in between 10years to 50years from the year of installation, the fluid flow speed should be in the range 2.69m/s to 3.2m/s and Partial pressure of CO_2 and Hydrogen Sulphide concentration should not exceed 0.2MPa and 0.1mol/L respectively

REFERENCES

1. Eberhart R, Kennedy J. A new optimizer using particle swarm theory. InMicro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on 1995 Oct 4 (pp. 39-43). IEEE.
2. Talukder S. Mathematicle Modelling and Applications of Particle Swarm Optimization. 2011.
3. Baker M. Pipeline corrosion. final report submitted to the US department of transportation pipeline and hazardous materials safety administration. Washington, DC, USA. 2008 Nov.
4. Nešić S. Key issues related to modelling of internal corrosion of oil and gas pipelines–A review. Corrosion science. 2007 Dec 31;49(12):4308-38.
5. Lee SH. Prioritizing Water Pipe Replacement and Rehabilitation by Evaluating Failure Risk (Doctoral dissertation, Texas A & M University). 2012.
6. Ossai CI, Boswell B, Davies IJ. Modelling the effects of production rates and physico-chemical parameters on pitting rate and pit depth growth of onshore oil and gas pipelines. Corrosion Engineering, Science and Technology. 2016 Jul 3;51(5):342-51.
7. Key issues related to modelling of internal corrosion of oil and gas pipelines – A review. Institute for Corrosion and Multiphase Technology, Ohio University, 342 West State Street, Athens, OH 45701, USA. Retrieved on 20th of January. 2016.

8. Gate Keeper Corrosion Modelling: Influencing Factors. A Technical Newsletter for the Oil and Gas Industries. 2014.
9. Ossai CI, Boswell B, Davies IJ. Pipeline failures in corrosive environments–A conceptual analysis of trends and effects. Engineering Failure Analysis. 2015 Jul 31;53:36-58.
10. Song F. Development of Tools to Estimate Actual Corrosion Growth Rates of Gas Pipelines. Rep. No. DTPH 56-08-T. 2011 Oct;3.
11. Caleyo F, Velázquez JC, Valor A, Hallen JM. Markov chain modelling of pitting corrosion in underground pipelines. Corrosion Science. 2009 Sep 30;51(9):2197-207.
12. Velázquez JC, Caleyo F, Valor A, Hallen JM. Predictive model for pitting corrosion in buried oil and gas pipelines. Corrosion. 2009 May;65(5):332-42.
13. Alam MN. Particle Swarm Optimization Algorithm and its Codes in MATLAB. 2016.
14. Kumar V, Minz S. Multi-objective particle swarm optimization: An introduction. Smart CR. 2014 Oct;4(5):335-53.