ADAPTIVE NEURO-FUZZY MODEL FOR OIL PIPELINES MONITORING IN A CLUSTER-BASED SENSOR NETWORK ENVIRONMENT

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ABSTRACT

Petroleum Products Pipeline (PPP) monitoring involves the regular checking of events on PPP with a view to providing timely information and response to events with significant deviation from the stipulated threshold of normal operations. Many PPP monitoring systems are characterized by lack of capabilities for intelligent monitoring, inadequate model for decision making, high rate of false alarm and limited data analysis capabilities. A Remote Diagnostic Centre (RDC) equipped with Adaptive Neuro Fuzzy Inference System (ANFIS) in a clustered-based sensor network environment is proposed for monitoring oil pipeline infrastructure. The aim is to harness human intelligence for PPP monitoring with its attendant gain of reduction in false alarm and promotion of timely response to PPP anomalies. ANFIS was designed based on Sugeno inference mechanism to learn from previous data as well as model the complex, vague and imprecise interaction existing in oil pipeline data. ANFIS controller was designed to facilitate real time processing at the RDC. The system was implemented using Java Development ToolKit (JDK) 1.7.0_25 as the front-end-engine and My Structured Query Language (MySQL) database as the back-end-engine. Matrix Laboratory provided the tools for ANFIS training, validation and testing. Oil pipelines data such as Pressure, Temperature, Inlet and Outlet Volumes as well as Flow-rate were collected from Pipelines and Products Marketing Company (PPMC), Port Harcourt, Nigeria and used to assess the functionality of the system. The System demonstrated 97% accuracy in the task of monitoring the state of petroleum products pipeline.

INTRODUCTION

Petroleum Products Pipeline (PPP) is a major oil and gas infrastructure. It is a vital medium of the energy supply chain in Nigeria and other developing economies of the world. The harsh environments where these pipelines are laid cause increase in probability of hazards and uncertainties triggered by seasonal soil texture, changes in environmental parameters and human activities. Accurate detection of anomalies in PPP can guide the mitigation of severe associated risks such as environmental pollution, fire outbreak, loss of lives and property (Mishra and Soni, 2011; Olawale *et al*., 2015; Udoh, 2016; Udoh *et al*., 2017). Many PPP are situated at isolated locations and the various activities on those pipelines such as pressure, flow-rate and temperature are time varying and require standby systems for monitoring. Therefore, a 24-hour daily human presence to monitor these activities is not guaranteed. Clustered-based Sensor Network (CSN) offer a plausible solution to timely, accurate and effective monitoring of oil pipeline infrastructure (Imad *et al.*, 2007). Many CSN models are limited by absence of intelligent tools for processing and derivation of inference from the simultaneously occurring and complex interactions of PPP events. These limitations could be conquered by incorporation of computational intelligent tools such as Adaptive Neuro Fuzzy Inference System (ANFIS) at the Remote Diagnostic Centre (RDC) for processing of PPP data. ANFIS provides the tools for learning from previous oil spillage data, resolving conflict of data imprecision as well as capturing uncertainties inherent in the inference processes.

Various methods exist for monitoring oil pipelines. These methods range from manual inspection to highly advanced satellite based hyper-spectral imaging (Carlson, 1993; Ellis *et al*., 2001). Pipeline monitoring is typically categorized into internal and external (Ariaratnam and Chandrasekaran, 2010).Internal approaches include computational pipeline modeling, pressure testing, flow rate testing, inline inspection and so on. External approaches include foot patrols along pipeline routes, aerial surveillance using helicopters, optical remote sensor methods, acoustic emissions, fibre-optic sensing, liquid sensing, vapour sensing (Olawale *et al*., 2015). CSN applications for pipeline infrastructure monitoring (Jawhar, 2007; Yuanwei and Ali, 2008; Harsh *et al*., 2010; Rahman and Hasbullah, 2010; Mohamed *et al*., 2010)used different sensors such as acoustic, vibration, temperature and pressure sensors to capture pressure, temperature and flow rate data on PPP for the detection of abnormal flow-rate. The combination of CSN technologies with information sharing and intelligent processing tools can address many, traditional safety, hazards and disaster issues facing pipeline and other petroleum infrastructure (Liu *et al*., 2015; Udoh, 2016) Many aspects of collaborative strategies of CSN with layered architecture that integrates autonomous cooperation can be found in(Park *et al*., 2010; Chen e*t al*., (2010). Imad *et al*. (2007) proposed a pipeline infrastructure monitoring framework to capture and transmit remote pipeline data to the base station. A data packet comprising type of data, sensing location, source address and measurement value was designed. Average of data collected from sensors over time were computed and sent to RDC via *General Packet Radio Service* (GPRS) center in a multihop fashion using ZigBee multi-hop routing algorithm. In (Adewuyi and Okelola, 2013), pipeline leak detection and control was presented using Neural Network (NN). The NN tools produced an intelligent system with learning capabilities for detecting the anomalies on PPP but were not capable of dealing with vague and imprecise data. Udoh *et al*. (2017), discussed a hybridized system for classification of pipeline activities using Fuzzy Logic (FL) and NN technologies. The FL system facilitated human-like classification while NN component assisted the system to learn from previous data of PPP activities. Each method of PPP monitoring has its strengths and weaknesses. This makes it difficult to have a single universally accepted approach. This work, therefore, adopts a hybrid approach which combines the cluster-based Wireless Sensor Network (WSN) technology and Computational Pipeline Modeling (CPM) approach using ANFIS. The CPM employs ANFIS with learning and imprecise data manipulation capabilities for holistic computation and inference on the rate of change of pressure, temperature or mass flow at different pipeline locations to guide intelligent decisions and response to anomalies at affected pipeline locations.

METHODOLOGY

The main building block of the ANFIS-based CPM system include Cluster-based WSN, Data Communication Network, Remote Diagnostic Centre with Human Computer Interfaces as depicted in Figure 1.

The clustered WSN is used to collect PPP potential data. The monitoring field comprises sensor nodes, organized into clusters, responsible for getting information into the system. The clustered scheme is suitable for short communication range and helps realize energy conservation with good traffic quality. Each node, with a position finding module, captures PPP data (pressure, temperature, flow rate, and oil volume), encapsulates them into packets, and collaboratively communicates their aggregate values through their cluster-heads (CHs) to the sink. The sink then transmits these aggregate values through the base station at the data communication network to the RDC for processing. ANFIS is a layered network bestowed with fuzzy logic imprecise data manipulation and neural network learning capabilities. The network is made up of adaptive and fixed nodes which accepts oils pipeline events crisp values and transforms them into linguistic variables with labels (Very Low, Low, Moderate, High and Very High) using triangular membership function.

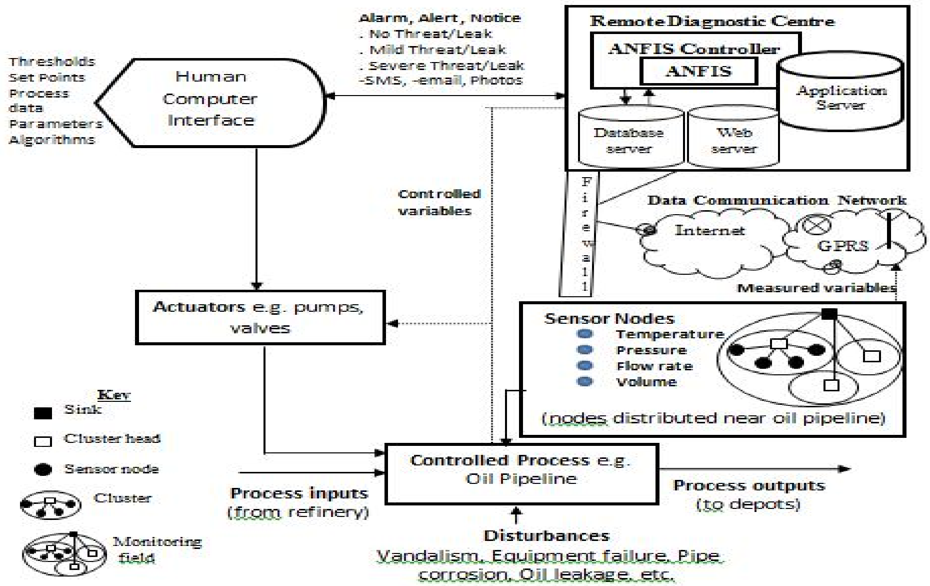

Figure 1. Architecture of the Intelligent Oil Pipeline Monitoring System

The ANFIS controller for monitoring oil pipelines is expressed mathematically thus: Given that $P_k, k = 1, 2, \dots, q$ is the set of PPP being monitored; $z_j, j = 1, 2, \dots, m$ is the set of PPP attributes captured by sensors; Z={pipeline pressure, inlet volume, temperature, flow rate, outlet volume } $x_i, i = 1, 2, \dots, n$ S_i,i=1,2,...,n is the set of PPP events (variations in PPP attributes) being monitored a $T_t, t = 1,2,\dots,h$ is the time specified for monitoring PPP, The confluent function δ_c , which returns the ordered samples of *ith* event for *jth* attribute of kth pipeline at time T_t,t_g is represented as follows:

$$\delta_c(x_{i,j,k}, T_t) = w_{i,j,k} \tag{1}$$

where $w_{i,j,k}$ is the ordered samples of events $x_{i,j,k}$ at time T_t .

Given that $S(v_{j,k})$ and $A(v_{j,k})$ represent the membership function of PPP attributes and ANFIS function respectively, which return fuzzy membership grade for *jth* attribute and the flow rate of petroleum products respectively on *kth* pipeline then:

$$S(v_{j,k}) = \begin{cases} \text{Very Low} & \text{if } v_{j,k} < 0.1 \\ \text{Low} & \text{if } 0.1 \le v_{j,k} < 0.3 \\ \text{Moderate} & \text{if } 0.3 \le v_{j,k} < 0.6 \\ \text{High} & \text{if } 0.6 \le v_{j,k} < 0.8 \\ \text{Very High} & \text{if } 0.8 \le v_{j,k} \le 1.0 \end{cases} \tag{2}$$

$$A(v_{j,k}) = \sum_{r=1}^{N} \overline{w}_r (f(S(v_{j,k}))) \tag{3}$$

where $v_{j,k}$ is the fuzzy value of PPP attributes, *r =1,2,…,N* represents rules that govern the input and output relationship on PPP based on Sugeno inference mechanism, $\overline{w}_r$ is the normalized firing strength of rules, *f* represents the ANFIS consequent parameters of PPP events. Let l_k and $D(l_k)$ represent the difference in inlet/outlet volume and corresponding membership grade of PPP for *kth* pipeline, then the ANFIS controller model, for monitoring *kth* Pipeline is given as:

$$P_k = \lambda(A(v_{j,k}), D(l_k)) \tag{4}$$

where λ is the oil pipeline status function. A rule set comprising 25 rules were formulated with the help of PPP monitoring experts for determination of oil pipeline status. Some of the rules are shown in Equation 5.

$$\lambda = \begin{cases} \text{No Threat/Leak} & \text{if } A(v_{j,k}) \text{ is Very Low and } D(l_k) \text{ is Very Low} \\ \text{Low Threat/Leak} & \text{if } A(v_{j,k}) \text{ is Low and } D(l_k) \text{ is Low} \\ \text{Mild Threat/Leak} & \text{if } A(v_{j,k}) \text{ is Moderate and } D(l_k) \text{ is Moderate} \\ \text{High Threat/Leak} & \text{if } A(v_{j,k}) \text{ is High and } D(l_k) \text{ is High} \\ \text{Very High Threat/Leak} & \text{if } A(v_{j,k}) \text{ is Very High and } D(l_k) \text{ is Very High} \end{cases} \tag{5}$$

Response to petroleum pipeline and remedy actions were based on the results of pipeline status function as depicted in Equation 5.

IMPLEMENTATION AND RESULTS

A dataset of 1500 data samples collected from Pipeline and Products Marketing Company (PPMC) in Port Harcourt Area office, Nigeria was used to assess the practical function of the system. The sample dataset comprising 20 items from the 1500 data samples collected is shown in Table 1.

Table 1: Sample Dataset

SN	Pipe ID	Time	Date	Pressure	Inlet Volume	Temperature	Outlet Volume	Flow Rate
1	PHAB01	8am	10/07/18	1436	1092	82	418	755
2	PHAB01	9am	11/07/18	1107	1369	61	1005	1187
3	PHAB01	10am	12/07/18	1401	1200	20	1100	1150
4	PHAB01	11am	12/07/18	1326	688	72	592	640
5	PHAB01	12am	12/07/18	1448	1010	73	432	721
6	PHAB01	1pm	12/07/18	1191	1519	37	1328	1424
7	PHEN02	2pm	12/07/18	1403	817	53	372	595
8	PHEN02	3pm	12/07/18	1441	1721	28	651	1186
9	PHEN02	4pm	12/07/18	1194	1727	23	148	938
10	PHEN02	5pm	12/07/18	1285	549	61	317	433
11	PHAB01	6pm	12/07/18	1234	795	52	713	754
12	PHAB01	8am	13/07/18	1248	1706	65	1611	1659
13	PHAB01	9am	13/07/18	1288	840	75	876	858
14	PHAB01	10am	13/07/18	1296	1321	17	1212	1267
15	PHAB01	11am	13/07/18	1254	1002	6	984	993
16	PHEN02	12am	13/07/18	1492	1134	23	1001	1068
17	PHEN02	1pm	13/07/18	1175	644	52	542	593
18	PHEN02	2pm	13/07/18	1189	656	40	559	608
19	PHEN02	3pm	13/07/18	1205	1492	45	1269	1381
20	PHEN02	4pm	13/07/13	1426	1261	91	1024	1143

Data attributes such as pipe segment identification (Pipe ID), time of data measurement (Time) and date of data measurement (Date) were not directly employed for determination of the PPP status but guided the response to PPP anomalies. The input attributes used for evaluation of the

PPP were pressure, inlet volume, temperature and outlet volume while flow-rate served as the output.

The dataset was divided into training, validation and testing datasets in the ratio of 8:1:1 respectively. ANFIS structure with four input indicators namely: Pressure, Temperature, inlet volume, outlet volume as well as one (1) output indicator: flow-rate which describe PPP behaviour were captured and trained as depicted in Figures 2a and 2b respectively.

Figure 2a: Oil Pipeline ANFIS Structure

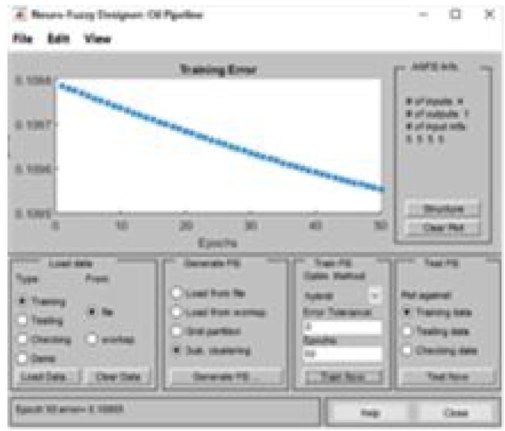

Figure 2b: ANFIS Training Window

The error value of 0.10955 between the computed and the desired output as shown in Figure 2b indicates that ANFIS is not well trained. Series of training sessions were conducted on ANFIS until the least Mean Square Error (MSE) between the computed and the desired output was obtained. ANFIS controller periodically (every 60s) checks the sensor data interface, reads and processes the data using ANFIS functions to determine the state of the Pipelines. The sensors data capturing process and data interface for reception of the captured data are depicted in Figures 3a and 3b respectively. The graphical results of PPP threat detection and difference between inlet/outlet volumes is shown in Figure 4.

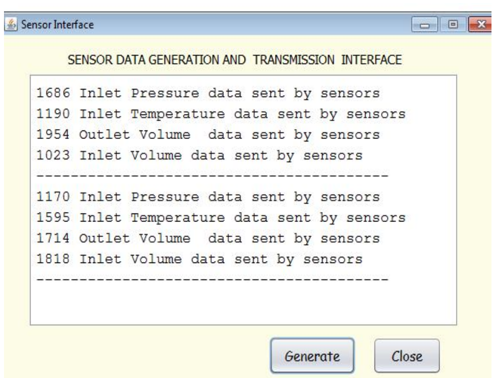

Figure 3a. Sensor Data Capturing

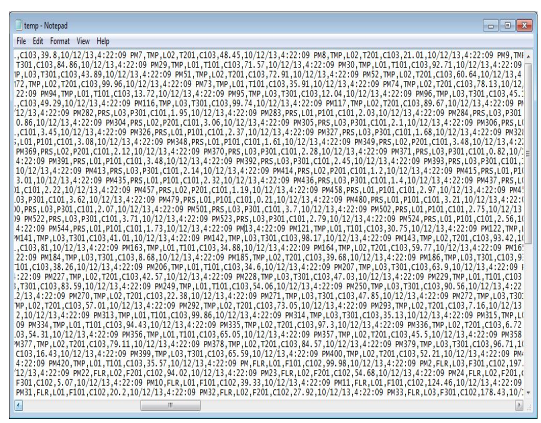

Figure 3b.CapturedData Interface

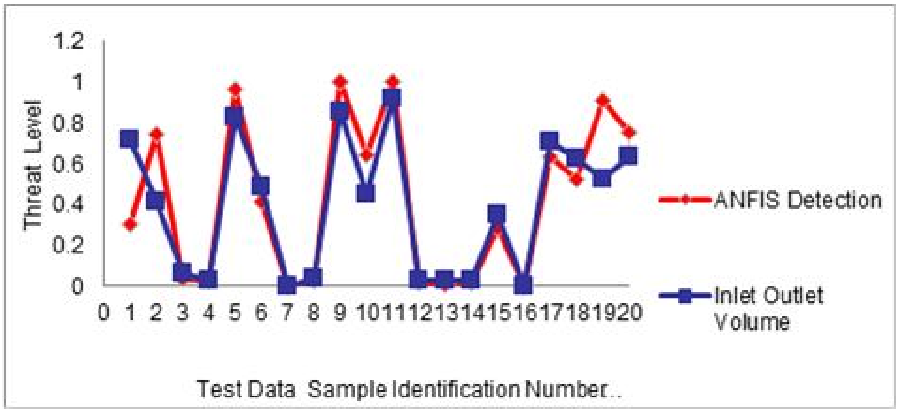

Figure 4: Graph of Oil Pipeline Threat Detection

RESULTS AND DISCUSSION

The performance of ANFIS at RDC in this study was compared with the use of Neural Network (NN) in Adewuyi and Okelola, (2013) and the use of Fuzzy Logic (FL) in (Udoh *et al.*, 2017). Evaluation indices were correlation coefficient *(r)*, inference time, Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE).The performance FL in terms of *r*, inference time, MSE, and MAPE were 0.734, 47.8, 0.0172, and 15.650 respectively. NN scored0.7407, 42.7, 0.0222, and 11.7836, respectively. While ANFIS with reduced fuzzy rules scored 0.97.01, 39.6, 0.0033, and 3.2742 respectively. NN performed better than FL based on inference time and MAPE. FL performed better than NN in terms of *r* and MSE. ANFIS with reduced Fuzzy rules performs better than NN and FL in terms of correlation coefficient (accuracy), inference time, MSE, and MAPE. These results indicate that using ANFIS at the RDC is better than using NN and FL alone in PPP monitoring operations.

CONCLUSION

In this work, an ANFIS was designed and incorporated in the RDC for complex data analysis and inference on oil pipeline infrastructure. The conceptual framework and formalism of PPP events monitoring with emphasis on the major functional components have been presented. The practicality of ANFIS platform in an environment characterized by Java, MATLAB and MySQL procedures has been demonstrated. A comparison of the use of different intelligent tools such as ANFIS, FL and NN at the RDC shows the superiority of ANFIS in terms of accuracy, inference time, MSE, and MAPE. Emerging technologies that offer superior performance and lower cost than existing CPM technologies could play an important role in increasing system efficiency. Future works shall employ self-organizing map to visualize and facilitate unsupervised network training at the RDC as well as evolutionary neuro-fuzzy controller to speed up convergence and optimize performance.

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