Leakage Detection in a Gas Pipeline Using Artificial Neural Networks Based on Wireless Sensor Network and Internet of Things

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***Abstract*— In this paper, a neural network-based method for leakage detection of a gas pipeline by using gas flow pattern is proposed. The pipe is divided in several segments and each segment is modeled by considering input/output pressure of the gas flow. The idea is to use a computer network based on Internet of Things (IOT) phenomena to gather all the required information for detection of the leakage point. In order to process the acquired data from the pipeline, a neural network is used and trained. As usual some of the data are used as training set to adjust the neural network weights and some other are used to evaluate the performance of the neural network based fault detection system. Practical data gathered from a real life pipeline is used to train the network to make sure that the proposed method is applicable real life projects.**

***Keywords*; Leakage Detection, Artificial Neural Network (ANN), Wireless Sensor Network (WSN), Internet of Things (IOT) , Gas Pipeline**

I. Introduction

Sixty percent of energy in the world is from oil and gas resources. So, to make transport independent and more reasonably priced, pipelines were adopted as a more economical means of transportation. Pipelines today transport a wide variety of materials including oil, crude oil, refined products, natural gases, condensate, process gases, as well as fresh and salt water. Today there are some 1.9 million kilometers of transport pipelines around the world. In many cases, due to the longer lengths and the difficult runs of remotely located pipelines, physical access may be limited. Pipelines can run through desert, across mountain ranges, along bodies of water, or be located underground or subsea, even at depths exceeding 1.6 kilometers. There exist the potential damage risk in gas pipeline such as impact of internal and environmental issues, the wave of pressure, fatigue cracks, tensile strength, material manufacturing errors, e.g. these potential damage risks can lead to pipeline leakage which can cause explosion in it. Therefore conducting a monitoring exercise on gas pipeline is vital. Fault detection in the gas transmission pipeline in particular the leakage detection plays a major role not only in safety and protection of the environment but also in economy of the projects. Thus leakage detection systems are subject to official regulations for example API^1 and $TRFL^2$. Leakage detection systems must be sensitive, reliable, accurate, and robust.

Leakage detection systems can be categorized into two major types; continuous and non-continuous systems. The non-continuous systems include: Inspection by helicopter, smart pigging, and even tracking dogs. Three approaches are possible to avoid leakage over continues system:

- The first, internal on the basis of physical mode such as mass or volume balance method, pressure point analysis, statistical systems, Real Time Transient Model (RTTM) based systems and Extended RTTM.
- Second, external implementation based on hardware such as sensors changing impedance, the volume of capacitor, fiber optic cable, acoustic sensor, infrared for image processing.
- Third Hybrid, the combination of first and the second for example acoustic analysis and pressure by balancing mass and volume.

Review of ways to detect leakage, industry establishes the combination of sensor technology for monitoring pressure, flow, compressor conditions, temperature, density and the other variables. The breakage starts from a pin-sized hole which can easily be detected by the means of instrumentation. For instance smart pig sends inside the pipe to detect welding effect and cracks of the sides using magnetic flux features and ultrasounds waves. The use of fiber optic cables for the monitoring of leakages is based on physical changes that occur at the leak site. One of those physical changes is a typical change in temperature profile. To detect such changes, the fiber optic cable is placed along the pipeline. However, use of this method is only possible up to limited lengths of pipeline and many reflections are required to plot a useful temperature profile Detecting gas leaks using infrared is made possible through video cameras featuring a special filter which is sensitive to a selected spectrum of infrared wavelengths. Certain hydrocarbons absorb infrared radiation from this spectrum. This makes it possible to detect the leaks as an image of smoke on the video display. On the other hand there are mechanical methods for the measurement of diameter and the thickness of pipe for detection of corrosion. Even though the above mentioned methods are exact nevertheless they have sophisticated mathematical description and its analytical knowledge **[5].**

Regarding internal leakage detection system Pressure point analysis is based on the evaluation of pressure drop or the

1. American Petroleum Institute
2. Technische Regel für Fernleitungsanlagen (Germany) (Technical Rule for. Pipeline Systems)

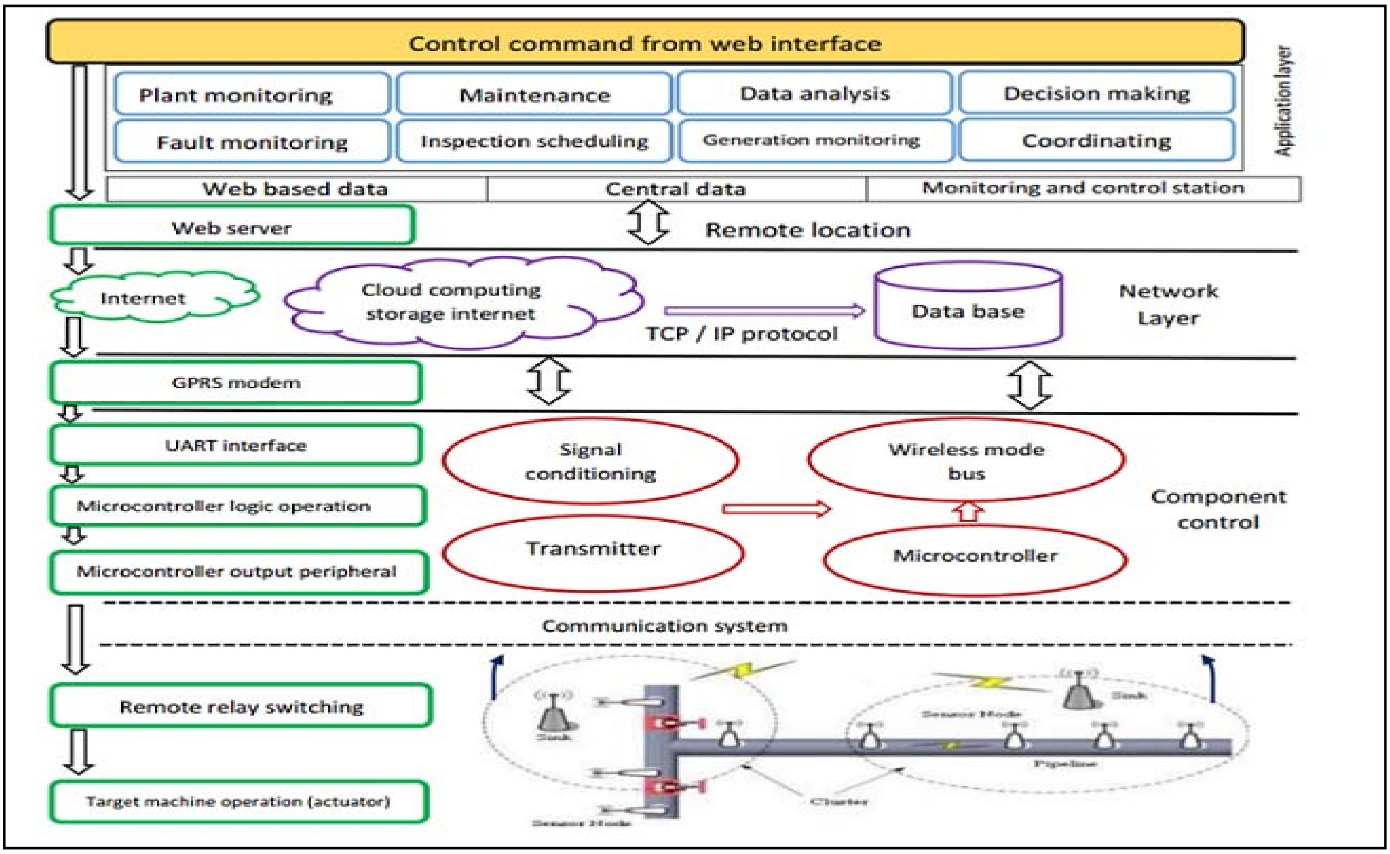

Figure 1. System architecture for leakage detection based on WSN and IOT

pressure profile measured at individual points. As an impulsive leakage brings up a characteristic change in the pressure drop, you can check whether the measured pressure drop, DP within a time period DT exceeds set thresholds. In addition to an upper threshold, a lower threshold for the pressure is also determined and if either one of these events occurs; the system triggers a leak alarm.

Another type is based on mass principle. According to this principle, mass in a closed system remains constant and is not changed by processes within the system. If the pipeline is considered to be a closed system and you compare the mass flow at the inlet and the outlet, the difference in a leak-free case should always equal zero. If, however, a leak occurs, the system has been opened and mass escapes. This results in a decrease in the measured mass flow at the outlet and an increase in the mass flow at the inlet.

Real Time Transient Model or RTTM systems can compensate for dynamic changes. To do this, they make use of basic physical laws which the pipeline must obey:

- The conservation of mass principle, which includes the density ρ, the time t, the flow velocity v and the pipeline location coordinates s
- The conservation of momentum principle, which includes the flow velocity v, the time t, the pressure P, the pipeline location coordinates s, and the pipeline friction fs
- The conservation of energy principle, which includes the enthalpy h, the time t, the density ρ, the pressure P, and the specific loss performance L

These physical principles precisely describe the stationary and transient activity of the flow in the pipeline. Using these equations flow, pressure, temperature and density can be calculated and integrated in real time for each point along the pipeline. These trends are also known as hydraulic profiles and accurately predict the true performance along the entire pipeline.

Artificial Neural Network (ANN) methods are used to model the pipeline in cases where generating mathematical and analytical models are complex. *ANN* is an appropriate candidate for leakage detection by using classification and estimation function. *ANN* is a robust method for facing noise which is suitable for real-time usage. There are different approaches for the detection of pipes leakage based on *ANN*. Authors in **[2],** have used acoustic sensor and analyze it by *ANN*. In a way acoustic sensors are sensitive on magnitude or velocity of wave (leak signal) due to characteristics of sound signals which are classified and trained with *ANN* and it is used as an *ANN* input and features of the signal from leakage analysis under the pipe pressure. Such signal after passing a filter is classified in several voltage signals by different frequencies and in output leakage is detected. *ANN* has so called number of training stages. Andre Maitelli and Andres Salazar in **[3],** have used an approach based on *ANN* by using sonic sensors for leakage detection. Such piezoelectric sonic sensors impose by providing forces from magnitude of flow changes.

Technologically point of view, *WSN* and *IOT* have attracted the interest of researchers whereas many industrial branches with different applications are used in the industrial *WSN*. There are variety of approaches in order to adopt advanced technology in communication and wireless instrumentation industry on basis of Electronic and Computer are common shortcomings in monitoring such as weakness of automation and Real-time is omitted. Regarding remote control based on Zigbee and WiFi protocols due to limitation of wide band frequency and low speed in data transmission that is appropriate small plant and cannot be used for massive plants for instance pipeline. Therefore these problems have tendency to lead us towards *IOT* which *TCP/IP* protocol. Structure of *IOT are three layers*. Sensors, voltage and current transducers are placed in the first layer. Microcontroller which is needed for the processing and wireless communication along with the servers also locate in this layer. The Second one is the network layer which consists of real-time processed-data and the database. The third is the application layer including suitable web services for the designed basis data collection which is illustrated on graphical display for monitoring of plant performance and exist control to reduce the decision making period. The structure illustrates in Fig.1. [6].

The clues in monitoring based on *IOT* for data collection such as pressure, temperature and flow which are heterogeneous and massive could bring out challenges in real-time decision making due to the fact that they are not reliable enough and cost making for measuring methods. In addition to influence of unexpected faults in the *WSN* relating to large quantities of physical environment dynamics, geographical distribution, generated heterogeneous data and the varied data during the transmission causes uncertainty. On *IOT* communication protocol between physical and application layers is *TCP/IP* [7].

Researchers in **[8],** have proposed one method with developing time compacting physical field for the latest data and restoration of *WSN* which is found on specific correlation features, time stability and the low rank structure relating to event reporting scenario. Pan, Liu and Lin in **[9],** have designed a mechanism that brings out data collection based on event for *Zigbee* in a tree shaped-structure of *WSN* including tree algorithm, assigned memory method event mode operation. Lu, Li, and Guizani in **[10],** have proved a safe approach for communicational smart grids and integrated data which is adaptive to digital watermarking for a safe communication. The study of authors in **[11],** is the application of *IOT* technology on the cloud computing. Aslan, Korpeoglu and Ulusoy in **[12],** have introduced a frame work for forest fire monitoring by using *WSN* and clustering route, the developed application layer, sensors deployment and the communicational protocol. Study of Islam, Shen and Wang in **[13],** is reliability and network security challenges in *WSN* that occurs in the factory automation and on the other hand cloud computing facing big data.

This paper presents a leakage detection method for gas pipeline based on Dynamic ANNs. For this purpose, wireless sensor network majored measure gas flow pattern use as the input signals for *ANN*. Multi layers of perceptron topology (MLP) were used for learning rules and offline training *ANN* including adjusting weights. The ANN was trained based on the error back propagation algorithm with partial derivatives. The input signals are dynamic neuron with delay time (ATDNN). The output signal is a certain value of identifying leakage specification considered as the input for leakage classifier to show whether the signal is a leakage or not. Fluid mathematical model was obtained from experimental data in real life pipeline. A computer network based on Internet of Things (IOT) phenomena was installed to aggregate all the required data to detect leakage points. In section II Mathematical model of pipeline illustrates. Section III presents proposed scheme. In section IV Simulation and results are shown. In section V conclusion and discuss future works.

II. Mathematical Model

The dynamic equation of fluid along the pipeline is as follow:

$$\frac{\partial Q}{\partial t} + gA\frac{\partial H}{\partial z} + \mu|Q|Q = 0 \qquad (1)$$
$$b^2\frac{\partial Q}{\partial z} + gA\frac{\partial H}{\partial t} = 0$$

Where:
H is the pressure head (m)
Q is the flow (m3/s)
z is the length coordinate (m)
t is the time coordinate (s)
g is the acceleration of the gravity (m2/s)
A is the cross-section area (m2)
D is the pipeline diameter (m)
b is the speed of sound (m/s)
μ = f/2DA where f is the Darcy-Weissbach friction coefficient

One leakage may cause discontinuity at point $\boldsymbol{z_1}$:

$$Q|\ z_1 = \lambda_i\sqrt{H|\ z_1} \qquad (2)$$

In a way that ***λi > 0*** depends on orifice aria / discharge coefficient. A pipeline with ***n-1*** leakage have ***n*** pair of the "equations (1)" with marginal conditions between each section of pipe as follow:

$$Q_b|\ z_1 = Q_a|\ z_1 + Q|\ z_1 \qquad (3)$$

In a way that ***Qa|zl*** and ***Qb|zl*** are the previous and the later ones and by having specified length of pipeline ***L*** and by supposing that the leakage is distributed alongside ***Z*** equally ***(Δz = L/n)***. Estimated partial derivatives from pressure and the flow is in a variable zone as follow:

$$\frac{\partial H}{\partial z} \cong \frac{H_{i+1}-H_i}{\Delta z} \quad , \quad \frac{\partial Q}{\partial z} \cong \frac{Q_i-Q_{i-1}}{\Delta z} \qquad (4)$$

In which index ***i*** regarding the variables in the beginning of part ***i*** and marginal conditions for every section it's as:

$$Q_i = \lambda_i\sqrt{H_i} \qquad (5)$$

With substituting "equation (4)" in "equation (1)" we have:

$$\frac{\partial Q_i}{\partial t} = a_1(H_i - H_{i+1}) - \mu|Q_i|Q_i \qquad (6)$$
$$\frac{\partial H_i}{\partial t} = a_2(Q_{i-1} - Q_i) - \left(\lambda_{i-1}\sqrt{H_i}\right)u_{t_i}$$

Where:
$H1 = Hri$ and $Hn+1 = Hro$ as system inputs parametric constants $a1 = g\pi r2n/L$ and $a2 = b2L/g\pi r2n$ with $n = 4$
$Uti = u\ (t - ti)$ is the unit step function associated with the occurrence time ti of the leak i.
In case there is no equal distribution, Δz is variable and parameters $\boldsymbol{a_1}$ and $\boldsymbol{a_2}$ are have equal pressures both at inlet and outlet affiliated to the gap between the leakages. In such a case $\boldsymbol{H_1}$ and $\boldsymbol{H_5}$ of a pipeline and $\boldsymbol{Q_1}$ and $\boldsymbol{Q_4}$ are measured flows all over the pipeline. Toward this four leakages in marginal condition is considered Fig.2.

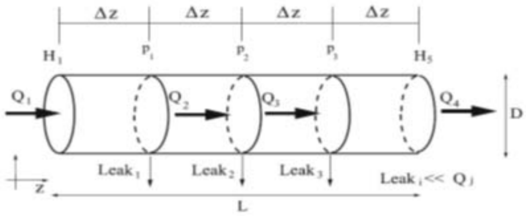

Figure 2.Distributed model of pipeline [1]

III. PROPOSED SCHEME

The proposed scheme of algorithm is illustrated in Fig.3. In the proposed method there is an *ANN* that identifies place of leakage along the pipeline. Time delay signals $\boldsymbol{Q1}$ and $\boldsymbol{Q4}$ are inputs of dynamic *ANN* which enhances the performance of *ANN*. The identification algorithm is divided into four parts.

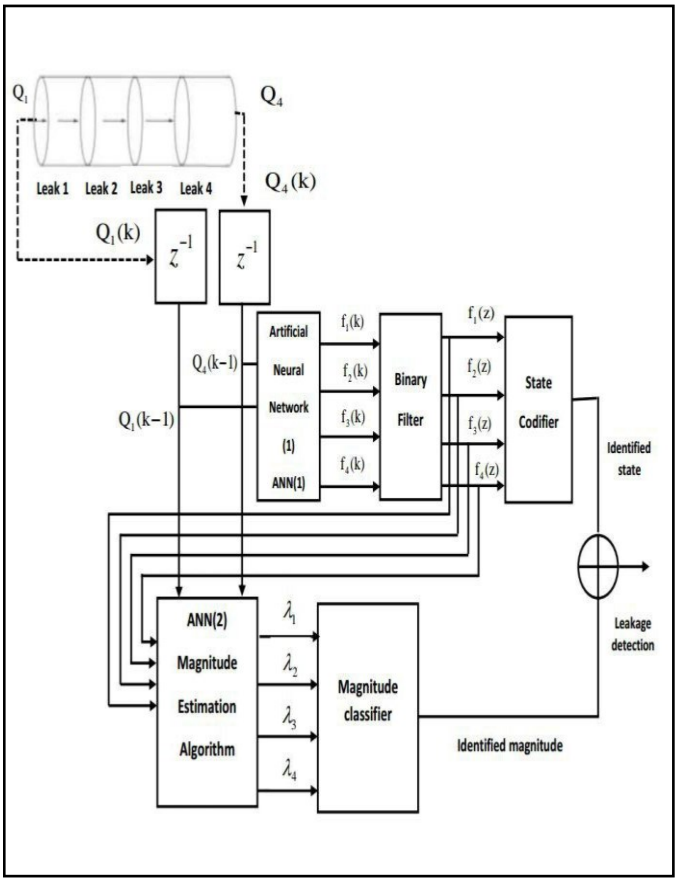

Figure.3. the structure of leakage detection scheme using ANN

The behavior of initial pressure signal, computing the magnitude of waves, computing output of *ANN* from the latest wave's energy and leakage analysis by a classification scheme.

The pipeline consisted of a 42" diameter 500m long mono chrome iron material of pipe. Gas leakages were triggered manually through the pipeline.

In this work the pipeline operated under nominal pressure of 90.7 bar, Temperature 55°C with the gas leaking through orifices about 3 mm in diameter. Flow, pressure and temperature signals per stream are interfaced to the plant DCS through a redundant Modbus TCP/IP link.

The *ANN* of Algorithm is feed forward multi-layer structure and back propagation algorithm is used for training the *ANN*. It is better to be used the least neurons and layers in addition the number of delays have the highest effect at the input signal.

The input layer uses tangent-sigmoid activation function and the output layer employs hyperbolic-sigmoid activation function. Leakage identifier is based on performing *ANN*. Detection is done by leakage states and upon the coming states the leakage will be identified. The description of figure.3 is as follow:

Two wireless ultrasonic flow meters were installed on the beginning and at the end of the modeled pipe generating data for training the neural model. The measurement of the inlet and outlet flows with the delayed-time are provided which they are the inputs of dynamic *ANN*. Discontinued model of a pipeline with length $\boldsymbol{L}$ is illustrated in Fig.2. The modeled pipe is divided into $\boldsymbol{n}$ sections with install deterministic observers upper the pipeline. It is created 2^n operational states. The accuracy of identified leakage depends on to the number of divided sections of pipeline. The bigger $\boldsymbol{n}$ would be the more accuracy. The set of $\{F_1(K), F_2(K), F_3(K) \ldots F_n(K)\}$ is the states of $\boldsymbol{n}$ discontinued sections of pipeline and output of *ANN* becomes activated by hyperbolic-tangent. The amount of $F\ (K)$ is from *0* to *1* that's why a binary filter is needed for making binary code and the estimation of binary fault. The set of $\{F_1(Z), F_2(Z), F_3(Z) \ldots F_n(Z)\}$ is the output of binary filter which have extracted the amount of *0* and *1* which in one side the binary to decimal converter block on the basis of simple digital rule, binary codes convert into a number that is the characteristic of operational state of pipeline. In other words the binary code of output filter goes towards the leakage estimation block which is the algorithm of the equation of the fluid dynamic. A leakage causes the discontinuation of "equation (2)" at point $\boldsymbol{i}$. In a way $\lambda i > 0$ is dependent on orifice aria and discharge coefficient and it's connected to flow and pressure of pipeline. $\lambda i \neq 0$ defines the leakage which is estimated from the sample of binary operational states. By analysis the behavior of the dynamic patterns, the difference of the operational states are observed. Then in the leakage block magnitude classifier allocate the amount of 0 and 1. As a result leakage and its place identify with combination of operational states and the magnitude of discharge coefficient. ANN at the output generates the specification of the leakage as illustrated "table I" which allocates a code to operational states and these codes are based on simple logical rules. The number of operational states that codes estimate depends on number of dividing sections of pipeline. Particularly, the pipeline is divided into four parts by the usage of two flow meters installed in inlet and outlet and three pressure gauge in the middle of modeled pipeline with 125 meters distance and there are sixteen operational states. There are hardware and software including sensor nodes which has ultrasonic flow meter encompasses Global Positioning System for gathering of the data and transmitting it to the control unit remotely and they are installed on specified points on the pipeline. Data transmits to microcontrollers by voltage and current transducers from the cluster heads which is equipped with GPRS/GSM module and internet protocol based on LEACH-TEEN routing algorithm which is event state because it is suitable for increasing the processors. Finally the graphical data is illustrated on the web pages on the computer.

Table I. Operation states of Pipeline

State	Activated leak	f_1	f_2	f_3	f_4	State	Activated leak	f_1	f_2	f_3	f_4
1	**No Leak**	**0**	**0**	**0**	**0**	**9**	**1 and 4**	**1**	**0**	**0**	**1**
2	1	1	0	0	0	10	1 and 3	1	0	1	0
3	**2**	**0**	**1**	**0**	**0**	**11**	**2 and 4**	**0**	**1**	**0**	**1**
4	3	0	0	1	0	12	1,2 and3	1	1	1	0
5	**4**	**0**	**0**	**0**	**1**	**13**	**2,3 and 4**	**0**	**1**	**1**	**1**
6	1 and 2	1	1	0	0	14	1,3 and 4	1	0	1	1
7	**2 and 3**	**0**	**1**	**1**	**0**	**15**	**1,2 and 4**	**1**	**1**	**0**	**1**
8	3 and 4	0	0	1	1	16	1,2,3,4	1	1	1	1

As for common methods of monitoring based on pressure and flow changes along the pipeline, there are disadvantages as well. One is lack of capability in exact point of the leakage and another is high rate of the fault alarms. For enhancing and optimization such research from hybrid method based on physical model, pressure analysis and dynamic flow and also implementation based on hardware such as WSN is proposed.

IV. Simulation and Results

A. Simulation of leakage detection algorithm by using ANN on matlab is done by the following procedure:

As mentioned before, the wireless sensors were installed on the upper of the modeled pipeline aggregate changes in the flow and is being transmitted via Modbus TCP/IP to HMI interfaced Distribution Control System (DCS). Such data is taken from the location of South Pars Gas complex. Several tests are conducted.

First, there is no initial data in the *ANN* and new data is given to it and operational of *ANN* is observed.

Secondly, noise of "**N**" is added to the entering flow signal.

On the third attempt the changes of flow were increased in different sections of pipe regarding TABLE.I and *ANN* with new data after changing in the discharge coefficient "λ" is trained again then the output is estimated the location of leakage accurately. In simulation the activity of leakage is displayed.

In Fig.4 the real operational states with 700 samples of flow rate are shown. In next test a leakage in the third part of pipe as in 4th state and then two leakages in the second and third parts of pipe in 7th state have occurred, however Fig.5 and Fig.6 are estimated operational states 1, 4 and 7 according to TABLE.I has followed as expected. It appears that dynamic neuron with a delay time (ATDNN) in the input of *ANN* enhances estimating operation and appropriate training. It is definite *ANN* has fully recognized altitude and its location. Therefore, no noise is observed.

B. Simulation Results

Simulation results illustrate faults during train processing and *ANN* structure depends on delay of flow signal. The *ANN* which has excessive delay, performs better. As it was expected having too much data concerning dynamic characteristic helps to the *ANN* taking appropriate samples from patterns. Detection of fault index "Estimated fault states relative to all the real states" it is the sign of *ANN* performance. By using delay signal and existing dynamic in the train algorithm of transition respond there is no need to pipeline middle point's data. In simulation more data will be obtained by dividing farther along the pipeline. Which improves the accuracy of leakage detection. In such approach estimation of leakage whereabouts is done by measurement of the input and output of flow and there is no need for the data of pressure and the amount of leakage. By analyzing the dynamic behavior of patterns, the difference among states is identified. The *ANN* using time delay recognizes tiny faults and this peculiarity is effective on cost because it uses less time for training. Industrial IoT embedded device should be able to adapt to the measurement needs of the thing being monitored or controlled. The IIoT can support continuous improvement and address previously unsolved problems to increase plant availability, safety, and reliability. By taking advantage of streaming data from sensors to quickly assess current conditions, recognize warning signs, deliver alerts and automatically trigger actions, Industrial IoT-based analytics solutions fundamentally transform identification and maintenance strategies.

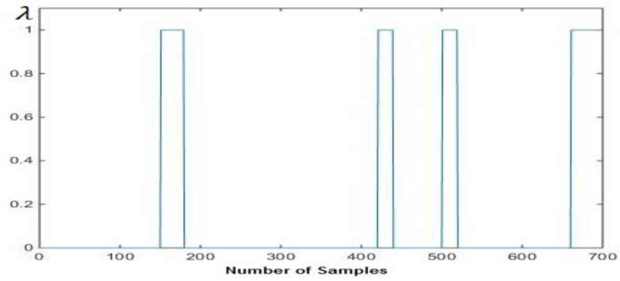

Figure.4. Output of ANN for real state operation

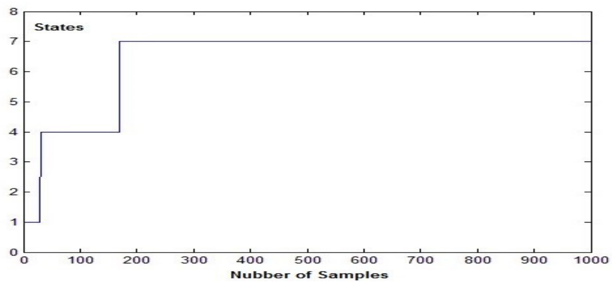

Figure 5. ANN prediction of Real state of pipeline

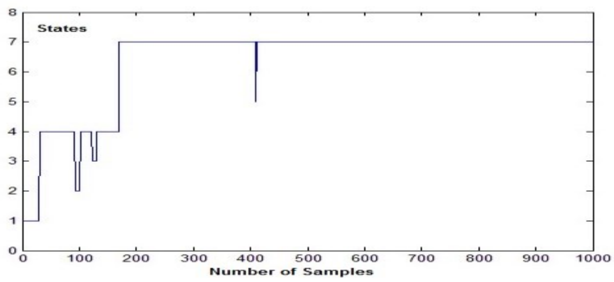

Figure.6. Estimated Operating States No.1.4.7 of the Pipeline

V. CONCLUSION

As can be seen there are different methods in leakage detection using ANN. The data analysis carried out by efficient neural network models could replace the human operator in the task of monitoring flow and pressure signal trends to warning the staff on the occurrence and inform the magnitude and location of the leakage. This methodology could be applied to monitor distribution networks of natural gas as well as industrial, commercial and residential gas pipelines in order to provide a safe operation and to avoid severe human health injuries caused by toxic gas leakages. There are several methods for leakage detection based on flow and pressure measurement but it's needed a nonlinear model of pipe for processing the data and simulate the flow of a gas with leakage. The numerical solution was validated with available experimental setup along the pipeline. Local control and monitoring is not economically reasonable for massive pipe transmission infrastructure. Thus using Wireless Sensor Network and Industrial Internet of Things are the most ideal and efficient approach for data aggregation and transmitting to control unit for the purpose of final decision making. A cloud-based control loop and Advanced Process Control (APC) monitoring system can be set up to monitor controls across the enterprise by an internal or external domain expert. With visibility and knowledge across sites, experts can alert and collaborate with site Subject Matter Experts (SMEs) and recommend actions when control benefit degradations are detected. Each site can benefit from earlier detection and faster resolution of problems afforded by a higher level of expertise focused on control performance. Approaches based upon remote and smart monitoring system in decision making with extensive, flexibility and automation in real-time architecture is the near future research to come.

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