Identifying Pipeline Leak by a Neuro Fuzzy System

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Abstract. **A methodology to identify pipeline leaks by using neuro-fuzzy techniques is here presented. A neuro-fuzzy system is developed to classify the running mode and to detect operational and process transients during petroleum fluids transfer maneuvers. The existing relationship between the transients and the mass balance deviations are discussed. This strategy allows an improved identification abnormal deviation due to a leakage, obtained throughout thresholds adjusted by the neuro-fuzzy as a function of the running mode and the classified transient level. The methodology is applied to a small-scale LGP pipeline monitoring case where portability, robustness and reliability are amongst the most important criteria for the abnormality detection system. The results are very encouraging with relatively low levels of false alarms and obtaining increased leakage detection with low computational costs.**

Keywords: Pipeline leakage detection, Pattern recognition, Neuro -fuzzy Systems.

I. INTRODUCTION

Pipeline is an efficient and economic transportation means for petroleum products. However, risks associated with accidental releases of transported product are still high [1]. This issue has motivated the development of many methods for leak detection, mainly based on process variables, i.e., pressure, flow rate and temperature, such as the volume balance method [2], or [3], where the importance of packing term in the transient flow is highlighted.

In the present paper, the high correlation between the inlet-outlet flow rate deviation and the operational transients is shown and it is the important fact considered defining the fault detection strategy. The applied strategy consists, at first, in the development of a classifier module that can identify the operational and process transients and to determine the current stage of the transfer process. Then, the output of this module is used by a Fault Detection module that will evaluate the inlet-outlet flow rate deviation, in order to detect a leakage or an abnormal operation condition, with a low level of spurious alarms.

A Fuzzy Inference System is used to solve the present problem by using a rule-base system developed from a database collected from a real process. The system was evaluated by a new data collected from the same process. And, good results have been obtained with increased leakage or abnormal situation detected. The low computational costs involved and low level of spurious alarms obtained are the most attractive items in the present system.

II. PROCESS DESCRIPTION

The petroleum products produced by a refinery are spread to distribution companies by pipelines. The Measuring Station (EMED) basically composes the control system that transfers petroleum derivatives to the buying companies. In general, main process variables arriving from the EMED, such as pressure, temperature, flow and density, are usually available in real time. In the destination, total flow, pressure and sometimes temperature are measured again.

Real data collected from a small LGP (Liquefied Petroleum Gas) pipeline is used for the present developments. The considered pipeline has 8-inch diameter and 2,000 meters of extension. Pressure, temperature and flow rate transducers are installed on both ends of the pipeline. For the tests here conducted, an expert initially evaluated this database. After modifying to able abnormal situations simulations, each stage of the transfer process and the in-out flow deviations were classified.

The present paper will focus in the monitoring of the LPG transference process, where often operational transients arouse larger complexity. During this transference process, the pipeline inner pressure gradually rises while the LPG receiving drum is filled. When the LPG drum is completely full, then transference process is switched to a new drum. At that moment, a sudden expansion is observed and an increase in the flowrate happens. During the drum filling process (steady state flow), there is only a small deviation in the total flow measured between the origin and the destination of the transference. The deviation is expected following mass balance model, and it is generated by the inherent uncertainties associated to the measuring process [4]. However, during the operational transient related to the receiving vessel switch procedure, the deviation here observed rises to significant values. This is mainly motivated by the line pack effect accounted by the mass balance model, due to diverse responses from measuring devices and by eventual lack of synchronism in the data acquisition system.

Modeling these transients through deterministic methods is a rather difficult task. In the next sections, the system will be

modeled and the correlation between data captured during distinct operational stages, which will support the Neuro-Fuzzy System architecture and fault detection module development, will be analyzed.

III. Correlation Modeling and Evaluating

The mass conservation model states that any difference between the mass flowing in and out of a pipe, in a given time interval, must be analyzed as a function of the mass variation inside the pipe during this time interval. This mass variation is denominated line pack. If there is no leakage, the general equation might be presented as the function of the mass flow as shown in below:

$$(Q_O - Q_d)dt = dLP \qquad (1)$$

where, Q_o = Volumetric flow measured in the pipeline's origin; Q_d = Volumetric flow measured in the pipeline's destination and; dLP = Line pack during one measuring cycle interval.

Adding the uncertainty of the measuring devices, it can be rewritten as follows:

$$(Q_O - Q_d) = \frac{dLP}{dt} + \varepsilon \qquad (2)$$

where, ε = flow measuring devices uncertainty.

Assuming no leakage, from the Equation (2) above, it can be concluded that in steady state flow, the difference between the origin and the destination flow is equal to the measuring devices' uncertainty, and; during operational transients, the line pack is added to the measuring devices' uncertainty.

Figure 1 shows the typical behavior of different parameters in LPG transference, where (a) flow, (b) pressure and (c) deviation between origin and destination flow is depicted. Often operational transients in this process occur during the receiving drum switch procedure, and increased deviation is measured between the measured flowrates during these operations. And, it is emphasized in the present study.

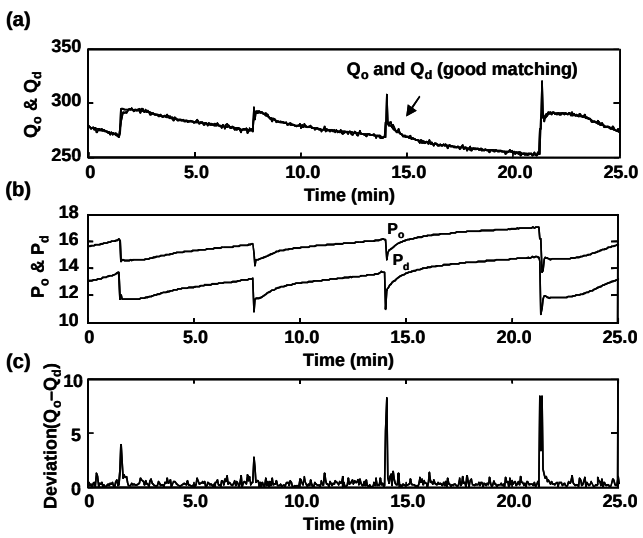

Figure 1. Typical behavior of LPG transference in terms of (a) flow, (b) pressure and (c) deviation.

Figure (2) shows the detailed behavior of these variables during a drum switching operation. The hydraulic unbalancing and differences between the flow measuring devices' responses, in the origin and in the destination (turbine and ultra-sonic, respectively), are emphasized.

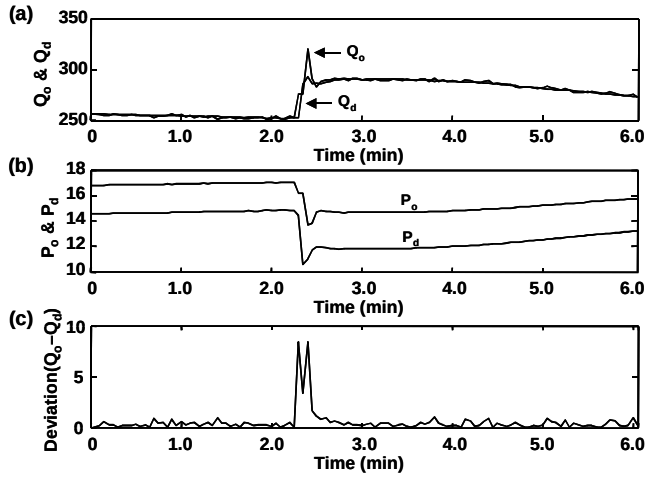

Figure 2. Detailed behavior of (a) flow, (b) pressure and (c) deviation during the switch operation.

In a conventional pipeline leakage detection system based on the mass balance model, if the above mentioned transient situation is not treated in an adequate manner, it usually generates a large number of false alarms [5]. Due to this problem, some variables, capable of identifying the casual operational transients, can be redefined as presented in Equations (3), (4) and (5).

Transient measured through average volumetric flow (Transqm):

$$Transqm(t) = abs\left(\frac{Q_m(t) - Q_m(t-1)}{\Delta t}\right) \qquad (3)$$

Transient measured through the origin-destination differential pressure variation (Transdp):

$$Transdp(t) = abs\left(\frac{(P_O(t) - P_d(t)) - (P_O(t-1) - P_d(t-1))}{\Delta t}\right) \qquad (4)$$

Transient measured through the modified hydraulic coefficient variation (Transcoef):

$$Transcoef(t) = abs\left[\frac{\left(\frac{Q_O(t) - Q_d(t)}{(P_O(t) - P_d(t))^2}\right) - \left(\frac{Q_O(t-1) - Q_d(t-1)}{(P_O(t-1) - P_d(t-1))^2}\right)}{\Delta t}\right] \qquad (5)$$

From the variables defined above, the correlation between the temporal series (Deviation x Transcoef; Deviation x Transdp and Deviation x Transqm) is found. The correlation is thus defined as in Equation (6):

$$Corr_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X . \sigma_Y} \qquad (6)$$

where, $\sigma_X^2 = \frac{1}{n}\sum_{1}^{n}(X_i - \mu_X)^2$ and $\sigma_Y^2 = \frac{1}{n}\sum_{1}^{n}(Y_i - \mu_Y)^2$

The result is shown in Figure 3, using the same data as in Figure 1.

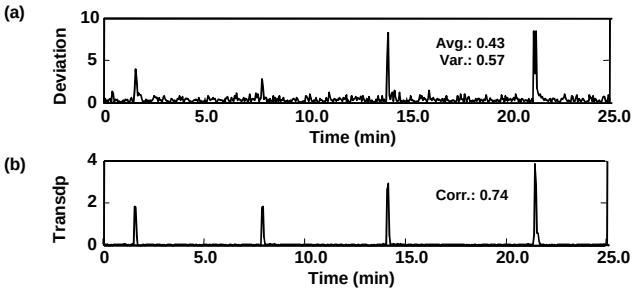

Figure 3. (a) Deviation and variables capable of identifying the casual operational transients, along with the correlation between these variables and the deviation: (b) Transdp.

As the correlation is relatively high, around 0.8, the deviation can be associated to any variable that represents a process transient. It should be highlighted that the correlation is computed through the series in Figure (3), which gathers the steady state flow and operational transients.

This statistic allows two main conclusions for the developed system: a) in the steady state flow, the correlation between the deviation and the transient is low and the deviation is statistically predictable, considering the low variance observed in the series, and; b) during operational transients, the correlation between the deviation and the transient is high, allowing the "isolation" of this condition for a specific treatment.

IV. Architecture Of The System

The architecture of the proposed system is divided into two modules (Figure 4). For the first module, initially the time series of measured process variables for transference is analyzed. And, based on the expert knowledge neural net structure is defined . In the second module, the developed nets in the first module are used to evaluate the process in real time.

The analysis of the transfer process is done by applying two neuro fuzzy nets (NFN), each one with four layers and built in accordance with definitions in [6]. The aim of the first NFN is to classify the operational state of the pipeline through observation of the mean flowrate of the transfer and the transient level observed in the process. The second NFN evaluates the deviation in the volume balance in the pipeline by using results from the first net. Figure 5 shows the basic architecture of the NFN. In the next sections the NFN will be shown.

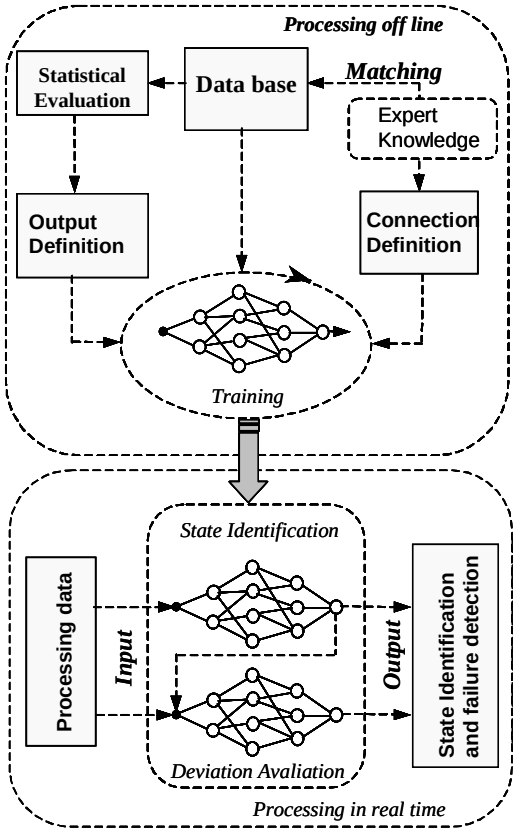

Figure 4. General architecture of the NFN system.

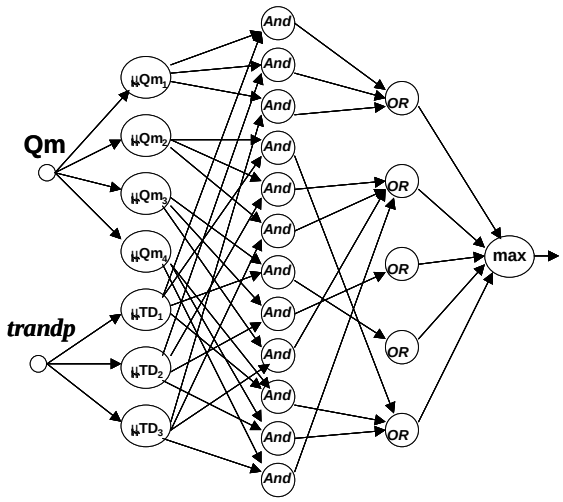

Figure 5. Layers of Neuro-fuzzy

A. Layers Definitions

Four layers compose the defined NFN. The first layer is composed by neurons activated with characteristic functions of input variables. The mean flowrate of the transfer process (Qm) and the transient calculated from the difference between pressures at inlet and outlet of the pipeline (transdp) defined by Equation (4) is used to NFN for State Identification. In the

NFN for Deviation Evaluation, the deviation in the volume balance (desv) and fuzzy output generated by the NFN for State Identification (Evalphase) referred to actual state of the pump. The Figures 6 and 7 show fuzzy functions used to define several linguistic variables associated to each input variable.

The parameters of the fuzzy functions (transdpa..g, qma...g e desva...g) are defined by statistical analysis of time histories and they are based in the observed functions max, min, standard deviation and means. These parameters are detailed in [7].

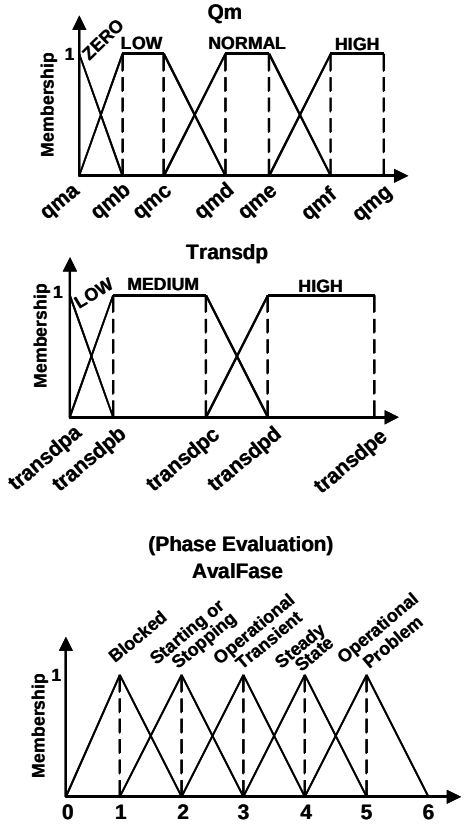

Figure 6. Input and output variables associated to the State Recognition Neuro Fuzzy.

Aggregation neurons are logical ones of AND and OR types defined in [6].

$$zj \_ \mathop{\mathbf{T}}_{i\_1}^{n} (wij \,\mathbf{s}\, yji) \qquad \text{(AND)}$$

$$zq \_ \mathop{\mathbf{S}}_{i\_1}^{n} (vij \,\mathbf{t}\, zji) \qquad \text{(OR)}$$

Where, S is the corresponding maximum s-norm and T is the corresponding t-norm of the product.

The second layer corresponds to the aggregation of fuzzy values of the input. Logical operator AND is used in the aggregation. All neurons in the first layer are connected to the second layer. For the NFN for State Identification, 12 neurons were generated in the second layer and, for the NFN for Deviation Evaluation 25 neurons were created.

Logical neurons of OR type composes the third layer. In this layer, only relevant connections to solve the problem were created, and they were defined by rules developed by an expert. Each neuron of this layer represents an output class for each NFN. The output variable of the first NFN is associated with the operational state of the transfer operation. This variable was denominated Phase-Evaluation. There are five linguistic terms associated with the system output: Blocked (B), Start-up and Shutdown (SuSd), Operational Transient (OT), Steady State (SS) and Operational Problem (OP). The output variable of the second NFN is the fuzzy linguistic variable DEVIATION, to which are associated five linguistic terms, corresponding to each of the failure diagnoses: Measuring Error Alarm, Measuring Error, Normal, Leakage Alarm, Leakage.

The fourth layer is denominated defuzzyfication layer and it consists of an isolated neuron which the activation function evaluates the maximum of input values from the third layer. The output defuzzyfication corresponds to the associated value of the linguistic output variable.

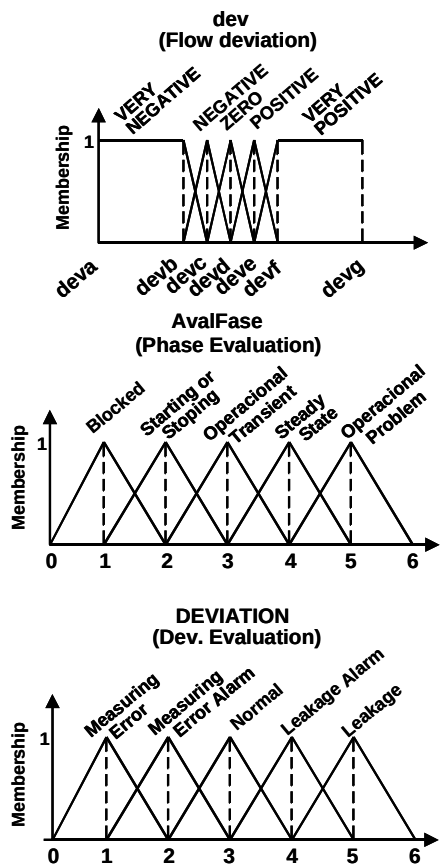

Figure 7. Input and output variables associated to the Deviation Evaluation.

B. Procedure to Generate the Nets

Following steps were applied to develop the nets and updating procedure of adopted weights during the process. This algorithm has been adapted from [6] and [7].

The specific functions defined in the item A were specified for each input variable.

C. Generation of Connections

Connection between neurons in different layers is now defined. Initially, connections for neurons between first and second layers were generated. For the connection with the third layer, rule bases defined by an expert were used [6]. The corresponding weights between first and second layer neurons were initiated with unitary value. And, the weights to aggregate the rules were initialized with zero. In order to obtain faster convergence in the process, initial attributed values for the weights can be optimized, however it was not the purpose of the present work.

D. Algorithm to Updating Weights

Punishing and rewarding proposal presented in the [6] was adopted here to update weights. The basic of this procedure is for each right step, the weight of each main involved neurons for the solution receives a positive increment. And, for each error occurred the value of these weights suffer a reduction. The following routine to update the weights were adopted:

- choose an point in the time series of date and interval;
- determination of activation neurons by this point;
- realize the fuzzyfication process;
- choose winner class and compare with the expected result (previously classified by the expert);
- update weights from the result of previous step;
- choose the next time series interval until to finish evaluation of the data bank;
- verify the obtained results;
- re-initiate the cycle until the convergence or until the iteration reach the maximum allowed.

V. RESULTS

LPG transference data set was obtained from an oil refinery. From this data set, three pumping operations previously classified as classical by an expert were used.

The proposed neuro fuzzy system was obtained from an approximately 15000 points database. After training of the system, it was tested with a set of 3000 points obtained from LPG transfer data of an actual maneuver. In this data trend leakage was simulated for developed system test purpose.

.During the test phase, the system was used to evaluate another real pumping operation, also classified by the expert.

The NFN that classify the operational state of the pipeline transfers were correct in 99,14% and 95,25% of the realized tests. An example of the result is shown in the Figure 8 where good answer could be obtained that for small leakage of 2% and 4%.

VI. CONCLUSIONS

The results obtained by the system are satisfactory, considering the low computational cost involved. It can be incorporated to the plant control and supervising system, with no need of a dedicated system. Establishing a new supervisory routine can eliminate the small variations' error through the process' continuous supervision.

Obtained results show that in typical classifying problems, neuro fuzzy nets have advantage if compared with deterministic models due to their capacity to learn general solution of a give problem from actual collected data and simplified rules.

In the present model, instantaneous fault detection was studied. The introduction of accumulated variables could make possible detection of smaller amount of leakage faster than in the present study. If combined with the present model can contribute to increase operational safety of transfer process in fluid transfers by pipelines.

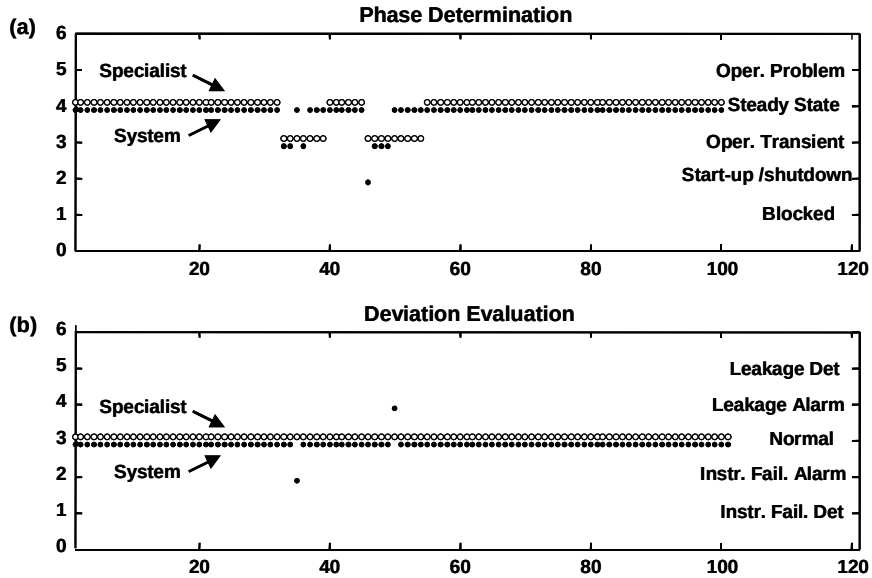

Figure 8. Comparison of the system and the expert evaluation for the (a) Phase Determination and the (b) Deviation Evaluation

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