An Intelligent Autonomous System for Condition-Based Maintenance- Case Study: Control Valves

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Abstract

Maintenance process generally plays a vital role to achieve more benefits to the enterprises. Undoubtedly, this process has a high value-added in oil and gas industries. Process owner expectations and new technology acquisition have been changing the mindset of domain experts to the new maintenance approaches and different newer methods such as condition-based maintenance models for improving the reliability and decreasing the cost of maintenance. Because of the high dynamic behavior of the gas and the instability of the input parameters, the need to apply a model with self-healing behavior is a serious demand in the gas industry. However, to the best of our knowledge, despite its importance, there is not any comprehensive study in the literature. In this paper, we present a new neuro-fuzzy model and a self-management control loop using real world data to meet the mentioned targets for a specified control valve in a gas refinery. ANFIS model is employed for the reasoning process which has six inputs (Inlet/outlet Pressures, temperature, flow rate, controller output and valve rod displacement), and one output that is a type of failure of the control valve and the most failures are considered based on domain expert knowledge. A suitable control loop is used to unceasingly monitor, analyze, plan and finally execute the process of prediction of failures. Due to undertaken improvement, there is a considerable change in reliability and financial indices. Moreover, the proposed approach is compared with two different methods. The results show that our proposed model comprehensively improves accuracy by 24%.

Keywords: Condition-Based Maintenance, Neuro-fuzzy, Autonomic computing, control valve.

1- Introduction

Maintenance is an aggregation of technical and related administrative actions intended to maintain an item/system in, or to restore it to a stable functioning state [1]. There are generally four main maintenance approaches: corrective maintenance (CM), preventive maintenance (PM), and condition-based maintenance (CBM) and the hybrid approach [2, 15]. In the CM approach, known as "run to failure" strategy, a device is allowed to fail. Then, the repair process is performed. This approach is suitable when the consequences and impacts of failures are small. In the PM approach, maintenance is scheduled in advance to prevent failures. It focuses on avoiding failures through replacing components at a particular time [2]. Then, in the CBM approach, the decision is made depending on the measured data. Based on data analysis, whenever monitoring level value exceeds a standard amount, a component is either replaced or repaired. Applying this strategy may lead to a considerable reduction in production cost. The optimization of the maintenance strategy is a trade-off between the cost of planned (PM/CBM) and unplanned (CM) maintenance interventions [3]. Finally, there is also a hybrid approach where CBM incorporated into one component with preventive maintenance (PM) and corrective maintenance (CM) on the other components of the same machine.
As a different stochastic model, Markov decision process and Bayesian networks are mostly used in maintenance prediction. One practical use is to employ a Bayesian network with conjugate priors to provide exact expressions for the remaining useful lifetime and obtain a set of expected operational cycle cost rate functions [18]. In recent years neuro-fuzzy vastly used in CBM since the algorithms are an assimilation of neural networks and FIS and can override the disadvantages of them. Neuro-fuzzy logic is easy and rapid to apply and particularly adaptive, lucid and highly flexible [19].

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Because of the high dynamic behavior of gas flowing in the equipment and the instability of input parameters of these equipment, applying a model with self-management behavior to meet the predefined targets is seriously demanding in the gas industry. However, to the best of our knowledge, despite its importance, none of the research studies cover the literature comprehensively, professionally, and precisely for a specified equipment.

Control valves are an integral device in oil and gas refineries. Also, they are one of the most overlooked devices in terms of maintenance. However, if not provided with proper maintenance, these units fail to operate to their maximum efficiency, which in turn leads to several performance issues. Generally, the most industries use corrective approach where a routine maintenance practice is conducted and scheduled maintenance program is considered. In this case, since the time of maintenance is the only criteria for the repair, so some equipment may be repaired although they don't require it. However, this approach usually leads to cost of downtime and maintenance. As a solution, condition based maintenance is used in this research to overcome to this problem. Here, maintenance of the control valves is rendered on the basis of the evaluation results of monitoring and testing equipment. Immediate maintenance or repairing action is taken in case of any discrepancies.

In this research, a new CBM model is designed and implemented for detecting and preventing some often failures in control valves using real data in a gas refinery and then extracting the frequent failures of the control valve, investigate the valve behavior. The data is collected from CMMS (Computerized Maintenance Management System) software running at the refinery for six months. Afterward, using the data and expert knowledge, we design and implement a self-management predictive maintenance system for the control valve. The proposed solution is based on the MAPE-K control loop to automatically analyze the behavior of a control valve and detect predefined failures in earlier condition before the defect causes complete disruption.

The main contributions of this paper are described as follows:

-Designing a self-management solution for predictive condition-based maintenance based on the MAPE-K control loop for the specified control valve.

-Utilizing the neuro-fuzzy technique as a decision maker in the MAPE-K control loop.

The rest of the paper is organized as follows: In section 2, related works and relevant literature is reviewed. Then there are some notations and definitions in section 3. The proposed framework and algorithm is described in detail in section 4. In Section 5, our solution is evaluated by comparing it with two other methods. Finally, in Section 6 and 7 we discuss all the results and conclude the paper.

2- Related Works And Literature Review

Several scientists have employed neuro-fuzzy to carry out a variety of tasks such as prediction and optimization and several models have been placed regarding various applications [4]. Although many investigators have extensively studied predictive maintenance in recent years, however, there are few studies about the control valves failures in gas refineries. In the rest of this section, the most important and relevant researches are reviewed in this field. Then, the most relevant studies have been assessed from various points of view [5-10].

Keizer et al. [8] prepared a broad literature overview of CBM policies for multi-component systems and occurrence of the dependencies. Friedrich et al. [5] presented an introduction into the possibilities to automate the maintenance process. Furthermore, another surveys [6, 7] also reviewed recent papers in successfulness of the CBM in manufacturing companies using vibration measurement and signal processing. Carnero [10] introduced the results of a survey of 35 Small and Medium Enterprises (SME's) in a region of Spain. Though some companies didn't have CBM, so this study assessed the level of the predictive program and where there was CBM, it analyzed its characteristics. They compared the results of this survey with the best practice as set out in the current literature and resulted that assessed SME's had very different results in almost all indicators used. Ahmad et al. [9] presented an overview of two maintenance techniques to determine how the TBM and CBM work toward maintenance decision making. Zhu et al. [11] introduced a new model for a single CBM component which gave opportunities for preventive maintenance. But for the deterioration process, they used both a random coefficient model and a Gamma process and developed an accurate approximate evaluation procedure for control limit policies. The key idea behind this approximation was that they pretended that the time points, at which preventive or corrective maintenance is executed, constitute renewal points as defined within renewal theory. Furthermore, Keizer et al. [12] proposed a multi-component, parallel condition-based maintenance (CBM) system with economic dependence and load sharing. They concluded that the redundancy resulting from the identical setting permits corrective replacements to be postponed without a system performance.

In a different approach, Do et al. [13] implemented a proactive model for perfect and imperfect actions on condition-based maintenance to check and consider the impacts of imperfect maintenance actions and to improve an adaptive maintenance policy, which can help to select optimally suitable actions at each inspection period. Liu et al. [14] incorporated side effect of the Wiener degradation process with linear drift into a condition-based maintenance policies with age- and state-dependent operating cost, which can be applied in various real systems to gain economic and societal benefits. Guariente et al. [16] studied the implementation of the autonomous maintenance in a company which supplies air conditioning tubes to the automotive section using Lean philosophy and by deploying a seven stage process. Furthermore, Lewandowski et al. [17] studied the way of handling the complex situation for the operational maintenance processes using an autonomous system as well as related spare part logistics in general and illustrated first concrete approach.

Table 1 summarizes some of the most relevant works related to the condition-based maintenance approaches based on applied techniques, performance metrics, case study, and reactive/proactive or autonomous policy.

Table 1: Statistics of the most relevant works related to CBM approaches

Ref.	***Applied Technique(s)***	***Performance Metrics***	***Case study***	***Reactive/ Proactive/ Autonomous***	***Single/Multiple components***	***Published Year***
[11]	Random coefficient mode Gamma process	Cost, Average Absolute Difference (AAD), Maximum Absolute Difference (MAD)	Lithography machines	Proactive	Single	2017
[15]	Threshold-based	Maintenance cost	Compressed air, generator and pumps	Hybrid	Multiple	2018
[13]	Gamma stochastic process	Maintenance cost, unavailability cost rate, inspection cost	Logistic industry	Proactive	Single	2015
[19]	Neuro-fuzzy system	Response surfaces	Aircraft engine	Autonomous	Single	2007
[18]	Bayesian Survival signature	System reliability, the unit cost rate	Manufacturing companies	Proactive	Multiple	2017
[12]	Markov Decision Process	optimal policy structure	Gas company	Proactive	Multiple	2018
[16]	Autonomous Maintenance Lean philosophy tools	Equipment Availability Overall Equipment Effectiveness	Automotive Component Manufacturer	Autonomous	Multiple	2017
[20]	Parameter Identification	Determine the remaining the lifetime of a component.	Industrial Machines	Proactive	Multiple	2016
[14]	Wiener process with linear drift	Optimum maintenance decisions	N/A	Proactive	Multiple	2017
[17]	CBM	Quality Enhancement	N/A	Autonomous	Multiple	2014
Our Proposed research	ANIFIS/ MAPE-K	Reliability and Financial	Control valve in gas industry	Autonomous	Multiple	------

Most of these studies mainly attempt to provide a model for CBM, employing techniques such as Gamma process [11] or Bayesian [18] which have proactive approach to the problem. In a different approach, some papers use neural network [16], [19] and [20], but they propose a general model to the CBM in industrial equipment.

In this study, a new model is proposed for a specified device so it can detect any abnormal condition of a control valve and therefore preventing it from any breakdown. Due to instability of gas entity and variety of input parameters, MAPE-K control loop is applied which according to obtained results we experience a considerable improvement.

3- Problem Formulation

The main goal in this research is identifying and analyzing the behavior of control valves in the gas industry so that it will be possible to detect failures in the

initial state. It should be noted that in all circumstances it has been assumed that the system is initially in a normal situation, then a failure occurs within an interval of time, and eventually the failure is detected and fixed. This sequence of generating and fixing the failure improves and enriches failure detection signal and also training of neuro-fuzzy network. In this section, equations and notations are described as shown in Table 2.
There are six parameters as inputs to the system, which are as follows:

- Inlet pressure: This is the pressure at valve input in the bar scale.
- Outlet pressure: This is the pressure at valve output in the bar scale.
- Controller output: This is a mini voltage from the controller.
- Flow rate: The amount of gas which passes through the control valve in a second.
- Temperature: that is the gas temperature in centigrade degree.
- Rod Displacement: this is the amount of valve stem movement.

Table 2: Notations and definitions

Notation	***Definition***
P_i	Valve Inlet pressure
P_o	Valve Outlet pressure
C	Valve Controller output
T	Gas Temperature
μ	Membership Function for the input value
Wi	Ignition Strength of the rules
$\overline{w_i}$	Normalized Firing strength
pi, qi, ri	Consequent Parameters
F_T	Failure Type as Output
S	The standard deviation of data
TA_T	Vector of Initial Learning Rates to be tested
R_T	The vector of rules to be tested
η	number of tests
E_P	number of epochs
Ai, Bi	Fuzzy sets
Y_i	Input value

4- Proposed Framework And Algorithms

In this section, our proposed framework and algorithms are explained in more detail. The proposed autonomous framework for condition-based maintenance makes use of ANFIS. The conceptual framework shows which components our system has and how they relate to each other, as shown in Figure 1.

4-1- Autonomous Systems

Autonomous systems act as a self-management component to detect errors preventively and make the appropriate decision to repair automatically. As the mastermind, MAPE-K control cycle make an autonomous system that consists of four components, as it is depicted in Figure 1; Monitoring, Analyzing, Planning, and executing Phases, which are described briefly in the following:
- **Monitor Phase**: In this phase, data that are produced by the sensor, meters, and gauges are gathered and filtered.
- **Analysis phase**: This phase acts as a signal modulating and transmitting component of the information obtained from the monitor phase.
- **Planning phase**: As the brain of the autonomous system, in this phase ANFIS is applied to utilize and make the required decisions.
- **Execution phase**: In this phase, the decisions made in the planning phase are performed.
All the above mentioned phases store their results in the Knowledge to make further use in the future by the other components.

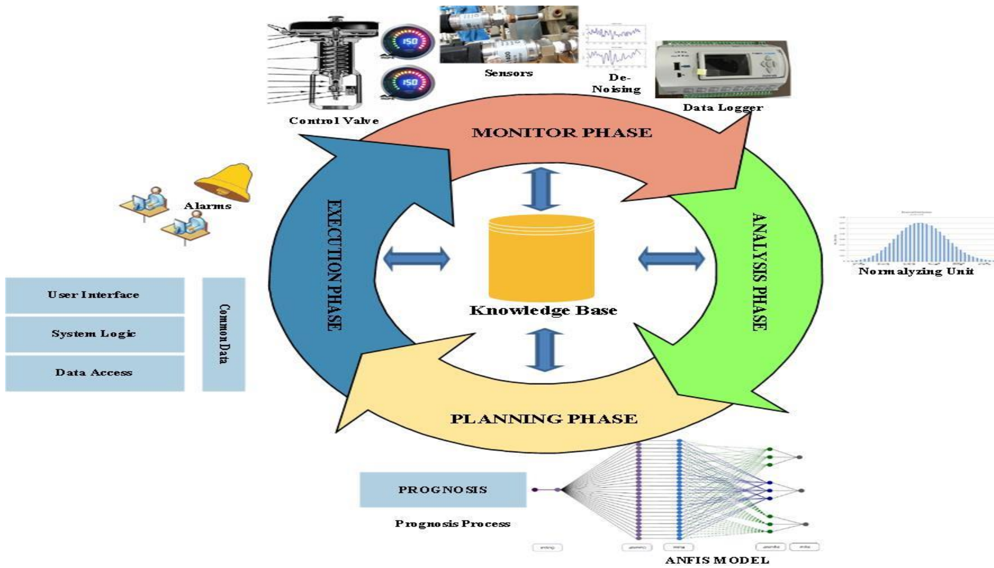

Fig. 1 The proposed autonomous framework for condition-based maintenance

4-2- Proposed Algorithms

In this subsection, the algorithms that are designed to predict, detect, and display predefined failure types are described. As mentioned earlier, the model uses the MAPE-K as control loop and ANFIS as a prediction tool to increase accuracy. In this research, it is assumed that the system (control valve) is initially in normal condition and then a failure occurs within a time interval. Therefore, at each time interval Δt, monitoring, analysis, planning, and execution are continuously repeated for existing data (algorithm 1- line 2-4).

In the monitor phase, sensors for temperature, pressure, flow, controller output voltage and displacement of the stem are used to receive and collect raw data. Then, these data will be stored in knowledge base engine that is a SQL database in this study. This data will be used as input to the next phase (line 6).

Afterward, in the analyzer component, aggregated raw data will be normalized (line 7). In the planning, which is the core phase, the prediction of the failure is done. In this step, using ANFIS model and training data, failure prediction is done (line 8). In the execution phase, in addition to setting up new basic data, the main outputs are displayed as the failure type (line 9).

Algorithm 1 shows the pseudo code for the four main phases of the MAPE-K for each time interval Δt.

Algorithm 1. Pseudo code for Autonomous predictive maintenance

1: ***Initialization***
2: ***while*** (the system is running and in the beginning of interval Δt) do
3: ***begin***
4: ***for*** (every gas particle in control valve flow rate Fv at interval Δt) do
5: ***begin***
6: ***Monitor*** (T, P_i, P_o, C, F, X at interval Δt)
7: ***Analyze*** (Input data as to be normal at interval Δt)
8: ***Plan*** (Inference using ANFIS as prediction of failures at interval Δt)
9: ***Execute*** (software components to retreive data and alert failure types at interval Δt)
10: ***end for***
11: ***end while***

A- Monitor Phase

This component is responsible to collect and aggregate all the necessary data as the system inputs. In this research, controller output voltage, temperature, Inlet and outlet pressures, flow rate and rod displacement of a typical control valve are considered as the system inputs. A data logger has to be employed (Figure 2- a) for data gathering and homogenizing inputs of the system. Figure 2-b, c, d show a real picture of the control valve associated with all sensors and cables after installation. The data logger uses XML format (although it can store data in some other forms e.g. JSON). It has Analogue and digital ports as input/output ports and then can transfer streams via a RS-485 serial port using Modbus protocol. An embedded Ethernet port may also be used for FTP/SNMP/SMTP protocols.

Fig. 2 a: Data logger b: Pressure/Flow transducer c: Rod displacement d: real control valve with all associated sensors

Generally, in this phase, the input parameters are aggregated and stored. To this purpose, some equipment such as pressure and temperature transmitters as well as all installed sensors and resistances are used, so that changes can be made to the valve without affecting the valve stem. These instruments are ultimately connected to the data logger observing the safety cautions and using the armored cables to the anti-explosion box. Afterwards, set up a SQL server to manage to store and to retrieve data and expert knowledge. Algorithm 2 shows the pseudo code for the monitoring phase of MAPE-K for each time interval.

Algorithm 2. Pseudo code for Monitoring Phase

1: ***Begin***
2: ***Read*** (Controller output C in interval Δt); /*controller output voltage Monitoring*/
3: ***Read*** (Temperature T in interval Δt); /*Temperature Monitoring*/
4: ***Read*** (Inlet Pressure P_i in interval Δt); /*Inlet Pressure Monitoring*/
5: ***Read*** (Outlet Pressure P_o in interval Δt); /* OutletPressure Monitoring*/
6:***Read*** (Flow rate F in interval Δt); /* Flow rate Monitoring*/
7:***Read*** (Rod Displacement X in interval Δt); /*Rod Displacement Monitoring*/
8: ***store*** **(gathered data);** /* storing in SQL database*/
9: ***return*** gathered value for (C, T, P_i, P_o, F, X)
10: ***End***

B- Analysis Phase

This phase consists of one subcomponent, namely the normalizing unit. There are four transmitters (e.g. two Pressures, temperature and flow) to modulate and transmit data signal in the form of electrical signal. In data logger then all data will be demodulated into a digital signal using. To do this, the device is configured so it can gather input parameters at desired time intervals.
Among the various normalizing methods, the model uses the Standardization method, which was first introduced by Saati to scale up the data in artificial neural networks, using equation (1)[25].

$$Normalized\ variable = \frac{x - mean}{S} \qquad (1)$$

In this equation, S is the standard deviation, and the variable X can be any of the input parameters (temperature, pressure, flow, and displacement rate of the stem).
Due to the existence of different scales for the received parameters (temperature: centigrade - pressure: Bar - flow: cubic meter per second and valve stem displacement: mm), it must be normalized (line 3).
Algorithm 3 shows pseudo code for this phase.

Algorithm 3. Pseudo code for Analysis Phase

1: ***Begin***
2: ***Normalize*** data (C, T, P_i, P_o, F, X) /* using Eq. 2*/
3:***store*** Normalized value /*using SQl database*/
4: ***return*** Normalized value

C- Planning Phase

The output of the previous phase is considered as the input of this phase. In this study, the ANFIS is employed to train the network, generalize the results to different states, and predict the failures. ANFIS as a hybrid method uses a parallel-distributed processing model and learning ability feature of ANN. ANFIS comprises of mainly two parts. The first one is the antecedent and the second part is the conclusion section, which is connected by rules [21].
ANFIS network is the feed-forward type which makes this adaptive network employ in a wide variety of applications of modeling, decision-making, and control [22]. For the learning process, a dataset is prepared which has been gathered from a gas refinery for six months. A total number of 57450 data records were considered in which 80% of the data were used for training and the remaining was used for testing (line 4 to 5). Figure 3 presents the train data in our ANFIS model.

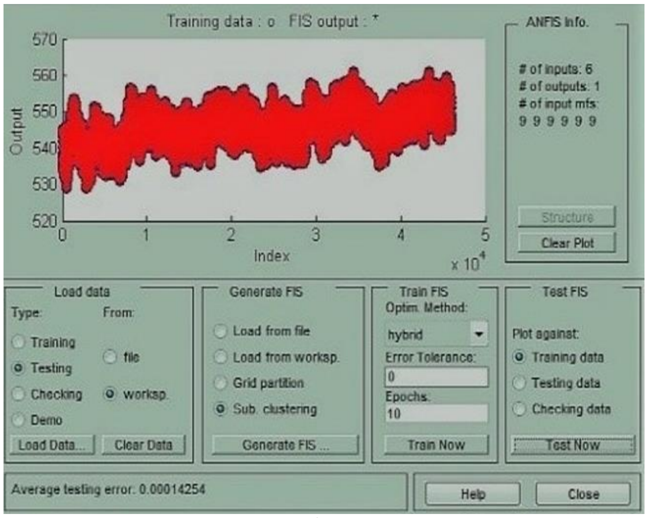

Fig. 3 Training data for the ANFIS model

FIS is generated by taking advantage of the sub-clustering method that is suitable for applications with a small number of inputs variables (less than 8). Training process fulfilled in 10 epochs. Error tolerance was kept zero for this process. After running the system, the value of 0.0014254 was obtained for the MSE variable, which was an acceptable value (see Figure 4)**.** Algorithm 4 shows pseudo-code for this step.

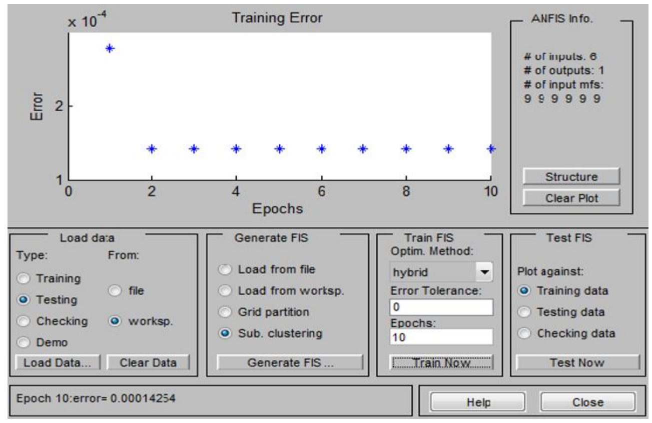

Fig. 4 System running and MSE obtained for ANFIS

Algorithm 4. Pseudo code for the Planning Phase

1: ***Begin***
2***: Input***: aggregated normalized data
3: ***Output***: Failure type
4: Training = 80% of Base
5: Testing = 20% of Base
6: Vector of rules to be tested R_T
7: Vector of Initial Learning Rates to be tested TA_T
8: η = number of tests
9: E_P = number of epochs
10***: for*** i ϵ TA_T do
11 ***for*** j ϵ R_T do
12 ***for*** l = 1 to η do
13 fuzzify inputs using trangular membership function by Eq. 2 /*Layer 1*/
14:check weights of each membership function (T-norm) by Eq. 3 /*Layer 2*/
15: perform pre-condition matching of fuzzy rules by Eq. 4 /*Layer 3*/
16: inference of rules and produce normalized firing rule strength by Eq. 5 /*Layer 4*/
17: sum up all the weights and defuzzification by Eq. 6 /*Layer 5*/
18: save the FIS with lowest validation error, the training error, output vector validation
19***:end for***
20:***end for***
21:***end for***
22***: End***

D- Execution Phase

This phase deals with a software component that can predict the occurrence of some pre-defined defects based on artificial intelligence and then alerts the user for suitable feedback. Algorithm 5 shows the Pseudo code for this phase [23-25].

Algorithm 5. Pseudo code for the execution Phase

1:***Begin***
2:***Input***: Failure type
3:***Output***: Approprate reports regarding deduction and domain knowledge
4:***fetch*** domain knowledge and rules and Common data /*from ANFIS model / Database/ common data */
5:***show*** failure type as report or list

5- Performance Evaluation

In this section, the effectiveness of our model is evaluated. In addition, in this study, MSE is used to determine accuracy and then as performance indices. Furthermore, some reliability and cost (financial) metrics are used that are explained at the end of this section.

Appraisal of the model is fulfilled by simulating the framework with two different methods (fuzzy SUGENO and neural network). To this purpose, at first the performance metrics are introduced which employed and then simulate the system with two various methods. Noteworthy, these experiments were all carried out on the same database though they may have had different training and test sets.

5-1- Performance Metrics

In this study two different approaches are employed for evaluation purposes. The MSE is used as a leading indicator, and MTBF, MTTR, and FR as a lagging indicator and then describe their short definition in the following.

- Mean Square Error (MSE):

This indicator measures the average of the squares of the errors that is, the average squared difference between the estimated values and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss.

- MTBF

This is a reliability term used to provide the number of failures per hours for equipment and is the most common inquiry about equipment's life span, and is important in the decision-making process of the end users as shown in the equation (2)[25].

$$MTBF = \frac{T}{R} \qquad (2)$$

where T is total operation time, and R is the number of failures.

- MTTR

MTTR is the time needed to repair failed equipment. In an operational system, repair generally means replacing a failed part. Equation 3 may calculate this indicator [25].

$$MTTR = \frac{Total\ Maintenance\ Time}{Number\ of\ repairs} \qquad (3)$$

- FR

Failure rate (FR) is another way of reporting MTBF, and it indicates the number of expected failures per (one million) hours of operation for a device.

- Maintenance Cost

Maintenance expenses are the costs incurred to keep an item in good condition or good working order. This includes maintenance materials, contract maintenance labor, and equipment rental.

- Downtime Cost

Downtime cost refers to the economic loss arising from downtime. The downtime attributes the financial damage to equipment maintenance or replacement at the refineries.

Figure 5 shows the results of the simulation done in the neural network. As it can be seen MSE is 0.026 that was measured by this method.

5-2- Experimental Analysis

In this section the effectiveness of the proposed framework is compared with two other approaches. i) At first, calculation of MSE is done for evaluating the prediction accuracy of the planner component by simulating the model with two different methods (fuzzy SUGENO and neural network). ii) Then calculate some reliability and finance metrics after implementation. Here we explain how to simulate the model, and afterward, describe performance indices.

- Neural Network Simulation

Using neural network fitting tool, 80% of data is input as training data, 10% for test and the remaining 10% for validation data. Table 3 shows the set parameters in the MATLAB environment.

As described early, neural networks are suitable candidates to fulfill CBM objectives. These algorithms have been validated on various data sets and were shown to possess good accuracy.

After simulating by this method, calculation of MSE equals to 0.0015, which shows a better value than neural network simulation.

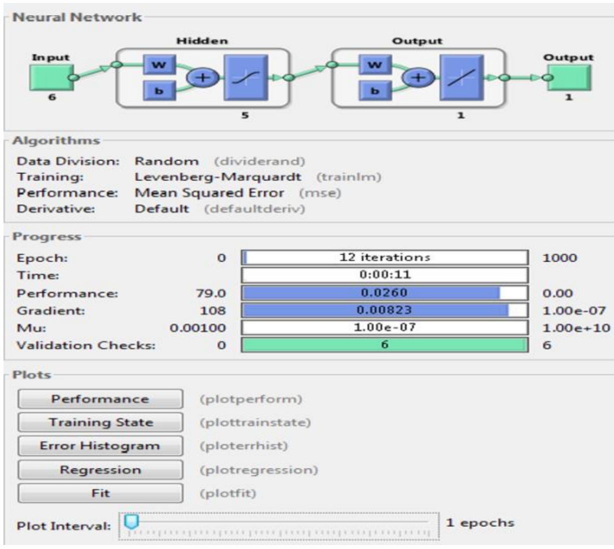

Fig. 5 Simulation result for the NN method

Table 3: Separation of data in ANFIS toolbox

Training Data	80%	45958 Samples
Validation Data	10%	5745 Samples
Test Data	10%	5745 Samples

- Fuzzy SUGENO simulation

As a second method for evaluating the model, fuzzy SUGENO is used. Sugeno is efficient for diagnosis applications, and the knowledge (rules) it extracts would be abstract for a domain expert as they are in a linguistic format. However, Sugeno uses a defuzzification strategy that limits the membership functions to obtain a Gaussian functional form. Table 4 denotes the set parameters for the simulation.

Table 4: Set parameters in Sugeno

Type	Sugeno
orMethod	prod
DE fuzzy Method	wtaver
impMethod	Prod
aggMethod	Sum
Input	6
Output	1
Training Data	80%
Validation Data	10%
Test Data	10%

6- Results

As it can be seen earlier in the proposed algorithm section, this error was 0.0014254 for MSE that shows the best performance among the other simulated methods. Table 5 shows the MSE value for the three methods.

Table 5**:** MSE value for different methods

Method	***MSE Value***
Neural Network	0.0260
Fuzzy SUGENO	0.0015
ANFIS	0.0014254

In a different approach and as lagging indicators, we validated our model by reliability and financial indicators. Reliability indices are those to monitor performance and efficiency. By implementing the proposed model, an improvement in all indices was observed. As it can be seen in Table 6, the overall outcome of implementing the proposed model results in an increase in MTBF and decrease in all other criteria that in refineries may have a significant benefit.

Table 6: Improvement rate in indices

Category	***Indices***	***Before Implementation***	***After Implementation***	***Improvement% (APP.)***
Reliability	MTBF(h)	11520	13090	14%
	MTTR(h)	282	218	22%
	FR	0.0505	0.0229	54%
Financial	Maintenance Cost(USD)	350	280	20%
	Downtime Cost(USD)	900	700	22%

It should be considered that this value is calculated for the specified control valve at the same time in the pilot plan.

7- Conclusion

In this paper, an intelligent autonomous system for condition-based maintenance is introduced which employed on control vales in a gas refinery. This model benefited from the real dataset as input gathered from various sensors (for more than six months) to run ANFIS as an analyzer, planner and decision maker and also MAPE-K as a control loop to present and implement a new model for condition-based maintenance in a gas refinery. Furthermore, this model utilizes expert knowledge to tune up the rules. This model is successfully implemented in a gas refinery as a pilot plan, and therefore it can be extended to other units and even other industries. There are some limitations to our research, many related to the sensitivity of the gas industry. Although this study is limited in specific equipment, it may be addressed by other researches in the future.

The proposed approach was evaluated using the real trending data of a control valve in the gas refinery. We concluded that our proposed model has many advantages compared to other policy since real monitoring of equipment's condition helps to cope better with the uncertainty. There are two groups of indices for evaluation in this study. Results show that there is a considerable improvement in all indices (from 14 to 54%).

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