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Development of Linguistic Rules Diagnosis of Failure in Centrifugal Pump for Use in Expert System

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Abstract
Operational failures in centrifuge pumps could be hydraulic or mechanical. However, most of these mechanical and hydraulic failures are connected cause of their operational nature and finding the right cause is due to considering numerous mechanical and hydraulic signs and parameters in pumps. On the other hand, due to non-linear and fluctuant behavior of pumps in the matter of time and not precise and clear data from a complicated system such as a petrochemical unit installations, investigating the failure possibilities in pumps by exact mathematical equations is so hard. However, the expert staff in maintenance could find the cause of failure by getting benefit of imprecise and verbal rules of "if-then" and the awareness of the non-clearance in system. However, it should be noted that this process takes time and also it is so dependent on the knowledge of expert staff, also human error can cause wrong decision-making and it declines reliability in the system. Therefore, this study is looking forward to find a collection of imprecise and verbal rules by using the reference book of "OREDA", also the pump handbook and the knowledge of expert staff in maintenance. With the acquisition of knowledge and Extraction of linguistic rules from taking effect between critical failure modes of mechanical and hydraulic parameters of process pump is created the relationship between these parameters and verbal rules, also by using a neural network of MLP category for the cases to train the neural network. Obtained results in companion with the average on accuracy, precision and recall parameters would be the approval of our method.

Keywords
Centrifugal pump, Troubleshooting, Failure mode, Acquisition of knowledge, Neural network

1. Introduction
Troubleshooting and detection of failures cause, in industrial systems, could be considered as the modern core technology, which making benefit of it, is increasing in both theory and practice by time. Also in recent years, applications of neural intelligence methods and expert systems design have been in the center of focus. Failure troubleshooting and its correction are strongly dependent on knowledge and experience. Therefore, sometimes the skill of technicians, engineers and operators would not be the solution. In these cases, expert systems could operate at least in the level of an expert and experienced technician whom his knowledge is beyond the guidelines and reference books. Therefore, the expert systems would be an efficient help in this matter for technicians and operators.
Troubleshooting could be considered as a reasoning process that defines the cause from observed effects (which are monitored by various sensors). From another aspect, troubleshooting is an effort for detecting the source of an unusual pattern in system by getting benefit of imprecise and limited information. A troubleshooting system should be able to state the cause of unusual cases through a rational reasoning. Many of incidents in petrochemical industry such as fire situation, explosion or flare the toxic gases are generally due to malfunction of parts in machines through processes (such as pumps, compressors, turbines, etc)[1].

Detection and investigating the root of these failures are so critical to prevent their occurrence also to develop the system reliance ability, improvement in process operation and its proficiency. After electro motors, pumps are the most consumption equipments in these industries, as an example in some refineries and petrochemical industries, more than 5000 different types of pumps are used to transfer hundreds of chemicals, such as raw and intermediate (sub) material also final products. Therefore, pump right selection, proper installation and maintenance could be so effective in proficiency also in cost decline for related units also development in performance of petrochemical industry. As an example, in some chemical process units (industries), 20% of raw price, 80% of BHP and 40% of annual maintenance cost are related to pumps. Annual costs of maintenance for pumps in chemical industries, in those cases which pump is a main equipment, are about 50% of pump purchase price [2].
Therefore, in recent years many of petrochemical complexes are trying to studypumps' operation, also their effect on process pattern in order to bring a structured and operational vision (sight) in order to develop a satisfying strategy for maintenance [3]. The most common method to categorize pumps is based on energy transition manner (method) to fluid. In this method, pumps are classified to two main categories: 1) dynamic pumps; in which energy transition to fluid is constant and 2) displacement pumps; in which energy transition to fluid is alternative. Dynamic and displacement pumps are naturally classified to several common sub-groups; centrifuge, special effect, reciprocating and rotary pumps [4]. Centrifuge pumps have a wide appliance in industries, especially in intermediate (sub) industries (oil, gas and petro), due to their cheap price of pump to one kilowatt of efficient produced power, constant and permanent flow(-rate) of fluid, high efficiency and relatively low maintenance cost [5].
Considering the importance of troubleshooting matter in industrial systems through expert systems, this paper tends to develop a base (infrastructure) for these systems, also to present a solution to design them. This infrastructure includes design and validation of several verbal rules (regulations) to troubleshoot a kind of centrifuge pump. Following parts of this paper include a review on titles' literature, definition of research method, presenting results also conclusion, which are arranged in four separate parts.

2. Literature review

One of researches related to automate troubleshooting in centrifuge pumps belongs to Sakthivel and his colleagues 2010. In this research, it is mentioned that considering the diversity and various applications for centrifuge pumps, it is crucial to categorize applications and the role of centrifuge pumps in designing expert systems. Their applied approach is according to constant monitoring of pump vibration also analysis on pump vibration condition. The outcome of this analysis is one of followed six states 1) pump ordinary condition, 2) bearing failure, 3) impeller failure, 4) gasquet failure, 5) simultaneous impeller and bearing failure 6) cavitations. In this paper, "The fuzzy decision-making tree and theoretical rough set" are used in order to develop relevant rules with help of undesired vibrational signals and definition of failure condition in centrifuge pumps. Results obtained from decision-making tree have been compared with theoretical rules of rough set. The conclusion is the preference of validation for all classifications by fuzzy decision-making tree is better than the second method (the rough set theory) [6].
In another study, by Muralidharan and his et. al in 2012, besides mentioning various applications of common centrifuge pumps in different industries such as cure, water and sewage, oil and gas also paper production, the importance of mechanical troubleshooting is emphasized. In these pumps, the performance of bearing and has a direct effect on pump performance. Defective bearing affect simpeller. Additionally cavitations phenomena is the main cause of many serious problems such as high noise and vibration etc. Cavitation phenomena could have worse and more undesirable effects such as weakening the hydraulic performance,

damage to pump due to erosion and vibration. Vibration signals are widely used to monitor the condition of such pumps. Damage is recognized by monitoring the vibration and comparing to other centrifuge pumps, which are operating in normal and failure condition. In normal condition, vibration is analyzed by FFT (fast Fourier transform) and piezoelectric transformers through vibration degree metering. The effect intensity could be interpreted through comparing with available records (background, history) of pump. Interpretation of process vibration trembling is complicated and needs professional learning, mostly investigating and analysis of unique frequencies in vibration signals could benefit the troubleshooting of mechanical parameters or a particular deficiency. By recognition of these frequencies and their harmonies, the analyzer could be able to detect the cause, location and source of failure. In this matter, machine-learning system could be useful to accelerate the error detection process and finally increase the availability rate in machine. Muralidharan and his co-workers used two bearings of KBS6203 model, one bearing was just fresh, and the other bearing was artificially damaged in order to cause controlled deficiency. Also two impellers with diameter of 125 mm made of cast iron were used, similarly one impeller was just fresh, the other one was artificially damaged in order to cause controlled deficiency [7].

Azadeh and his colleagues, in 2010, studied operational obstacles in centrifuge pumps from two aspects; hydraulic and mechanical, in a petrochemical complex. They mentioned that many of these mechanical and hydraulic failures are naturally relevant and definition (etiology) of the right cause of failure needs considering various mechanical and hydraulic signals and parameters [8].

Their approach of study is knowledge acquisition and extraction of verbal rules and regulations in order to develop a base for fuzzy intelligent troubleshooting system regulations, through considering mutual effect of critical failure states on hydraulic and mechanical process parameters in pumps such as flow-rate, discharge pressure, NPSHR, BHP, efficiency, vibration and temperature. In order to validate the presented intelligent system for troubleshooting in their study, centrifuge pumps of one petrochemical complex are used and their results are compared with results from current (available) failure reports in maintenance unit in mentioned complex. Obtained results validate the proper (acceptable) performance of this troubleshooting intelligent system [8].

In 2000, Fonseca and Knapp presented a new structure to perform maintenance according to RCM (reliability centered maintenance), in prior phases of industrial chemical processes design [9]. In this study, to evaluate the possibility of failure states incidence in different equipments in a chemical process, fuzzy reasoning algorithms are applied. In addition, an approximate reasoning algorithm is designed to prioritize failure states for different equipments in process, according to the effect of each deficiency on product and adjacent machines (machinery).

LUBRES expert system provided by Qian et. al. In 2008, in the monitoring and detection of abnormal conditions in the lubrication oil refining process to help workers and refinery operators [10].The structure of this system consists of a knowledge base and the inference machine. This paper presented a new strategy for the resolution of conflict situations (sort introduction strategy and the strategy chosen or default rules of the knowledge base memory). Knowledge acquisition mechanism based on empirical knowledge and validation of a table, which is directly based on the graphs. To develop the system of C ++ Builder and SQL Server 2000 is used. The expert system is used in actual case to monitor fault detection and cause analysis of possible errors in the lubrication oil refining process for a year.

3. Research Methodology

The Pump in this study is a centrifugal pump with low fluid transfer Service Stripper column bottom is the type 250*200 UCWM. The pump is designed according to API 610 standard. The standard requirements

Centrifugal Pumps for use in the process of Oil, Gas and Petrochemical has identified and is authenticated By America National Standards Institute (ANSI). It is technically equivalent to ISO 13709 which is the international standard. Working conditions characterized by the Performance curve of a centrifugal pump, including the Head of the curve, the Efficiency curve, Brake Horse Power curve and the NPSHR curve, is shown. Therefore, in this study, the parameters of "Flow Rate or Q", "Discharge pressure" and "NPSHR" as the hydraulic parameters and parameters of " Brake Horse Power," " efficiency," " Vibration " and "Temperature" represents the mechanical parameters the pumps are considered. The pump Data Sheet, including the pump equipment and its operating parameters is shown in Figure 1.

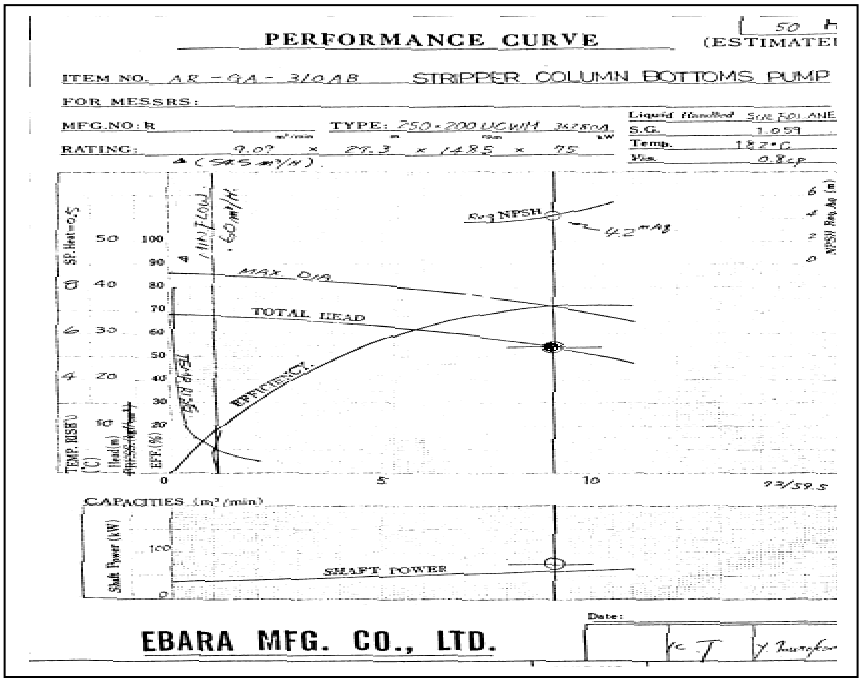

Figure1. Pump characteristic curve GA-310A

In this study, classified OREDA[1] information database is used. OREDA, failure modes based are Classified on the seriousness of the state into four groups critical failure, a Degraded failure, the Incipient failure and Unknown failure mode. In this study without the whole question is reduced, the failure modes classified in OREDA for centrifugal pumps (centrifugal pumps and more specifically to the service of process oil), which has the highest rate of failure modes are selected for review. The equipment specifications and operating parameters specified in the pump Data Sheet characteristic curves produced by the manufacturer of pumps, pump PFD diagram simulation process and expert engineers, maintenance personnel and the pump operating range was specified.

According to the OREDA book for the pumps, the critical failure modes, the leakage rate of 49.08, 9.82 and vibration and noise Spurious stop rate of 4.91 have the highest rate of incidence rates. In order to assess the damage in three centrifugal pumps using failure data, OREDA failure data tables, parts and causes of failure are the most affected parameters in the event of the failure modes which are identified in Figure 2.

[1]Is an enterprise project data collection has started its activities since the early eighties. The main objective OREDA, collection and exchange of data reliability (reliability) and maintenance of oil and gas

OREDA-2002 205 OREDA-2002

Taxonomy no	Item
1.3.1.15	Machinery Pumps Centrifugal Oil processing

Population	Installations	Aggregated time in service (10^6 hours)		No of demands
		Calendar time *	Operational time †	
5	2	0.2037	0.1302	85

Failure mode	No of failures	Failure rate (per 10^6 hours)					Active rep.hrs	Repair (manhours)		
		Lower	Mean	Upper	SD	n/t		Min	Mean	Max
Critical	15*	0.34	75.95	282.27	104.22	73.62	14.6	2.0	14.9	80.0
	15†	0.55	98.46	351.20	129.75	115.23				
Breakdown	1*	0.27	4.96	14.74	4.91	4.91	-	-	-	-
	1†	0.05	7.18	24.72	9.11	7.68				
External leakage - Process medium	10*	0.25	50.58	184.90	68.31	49.06	11.2	2.0	11.2	20.0
	10†	0.45	66.25	228.19	84.11	76.82				
Fail to start on demand	1*	0.27	4.96	14.74	4.91	4.91	6.0	6.0	6.0	6.0
	1†	0.05	7.18	24.72	9.11	7.68				
Spurious stop	2*	0.31	9.99	30.35	10.46	9.82	3.5	3.0	3.5	4.0
	2†	2.28	14.56	35.69	10.86	15.36				

Figure2. Page 205 of OREDA: failure rate

A process in which the pump is activated, the process is Sulfolane. In this process, impurities mixed with hydrocarbon solvents Sulfolane input, naphtha, distillation tower and separated with high purity aromatics (C6 - C9) such as benzene which are extracted.

In this study, to obtain reference points, the normal operating range, the maximum and minimum allowed by the pump processing parameters with regard to the Equipment P & ID, PFD in which the pump is located has been simulated by Aspen HYSYS software, Figure 3. Aspen HYSYS Software is common software used to simulate chemical processes, particularly in the oil, gas and petrochemical. The software has the ability to design, monitor and evaluate the economic performance of the process. The software shows the main Equipment of process and how the materials are flowed displayed. Reactors, Towers separation (such as distillation, extraction, etc.), tanks, heat exchangers, filters, dryers, pumps, compressors and the like are the most important processing unit. pick the trends displayed [11-14].The equipment specifications and operating parameters specified in the Pump Data Sheet, Production characteristic curves characterized by a manufacturer of pumps, pump PFD diagram simulation process and expert engineers and maintenance personnel and operations of each of the processing parameters centrifugal pump Intervals are shown in this study. The range actually represents a fuzzy interpretation of each pump, which is processing parameters.

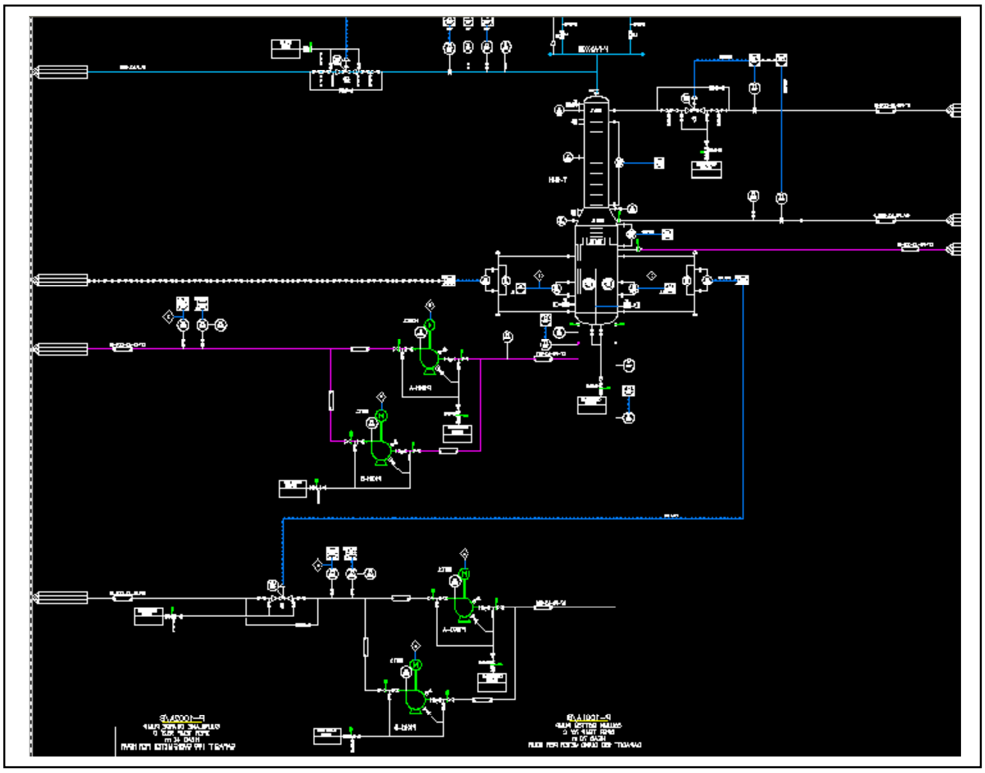

Figure3. Diagram PFD process Sulfolane Aspen HYSYS software

The model is designed to create a troubleshooting expert system for centrifugal pump according to (Figure. 4). 7 parameters of flow Rate, Discharge pressure, NPSHR, BHP, Efficiency, vibration and temperature are inputs and the development of pump FMEA models intended to determine the impact of the failure modes of operating parameters, rules extracted using similar language were the reference points and operating according to pump Data Sheet range are extracted. Then membership functions and rules of language development tool neural network, neural network and the average of the parameters of accuracy (Accuracy), precision (Precision), and recall (Recall), was carried out. The best neural network with the number of neurons in hidden layers was identified and the re- training and the results were confirmed.

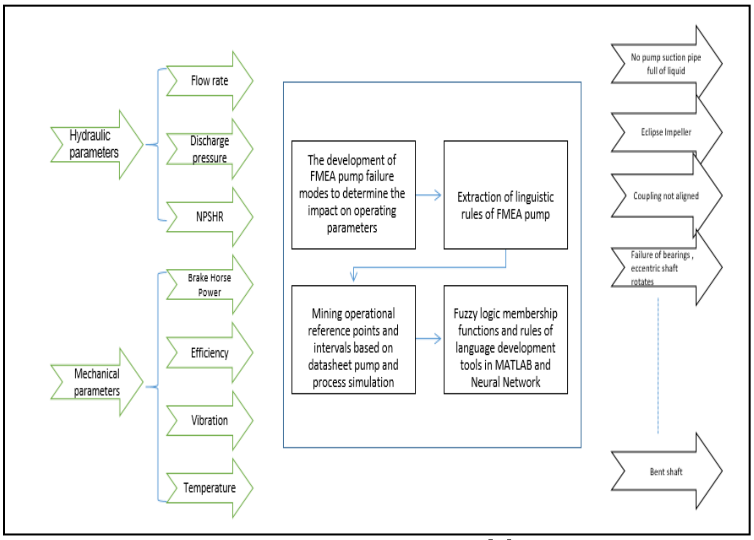

Figure4. Overview model

In order to establish cause and effect relationship between the pump failure modes and their causes as inputs Chart systematic analysis of failure modes, causes and effects (FMEA) are considered and their effects on process parameters pump is analyzed. Following, the review of FMEA methodology and its application in the study of language rules pump is applied in order to extract troubleshooting for centrifugal pumps, FMEA is a systematic tools based on a team work to define, identify, assess, prevent, eliminate or control the circumstances, causes and potential effects of a system, process, or service design used [15]. one of the best features of FMEA is the action measure rather than reaction measure which is applied to deal with defeat and failure, In other word it's a preventive action before the incident because in case a bad incident happens, usually a huge cost would be spent to remove bugs and crashes in the system. If for any reason an error is rooted in the design, the damage will be maximized, because a change in the design causes a change in productive tools and it will consequently causes repeated costs in designing products and processing. In addition, to enhance the word efficiency, the FMEA is applied before the error factor and process error occurs …! Because of the time and the cost which is spend on FMEA implementation it would be possible to apply all changes and edits in the design production and processing easily and with minimum cost.In fact, the FMEA minimizes problems and issues which is caused by Appling the changes in the system. Thus, therefore, the FMEA can be used as a tool for continuous improvement in production quality and services in companies in order to apply the analysis by FMEA the following steps should be taken, [15.16]

the system identification and its performance in this stage in order to simplify coming analysis, all necessary and unnecessary functions is considered.[17.18]

Identifying the major components and its performance: in this process, the main components and functions and their relationships should be determined (logical connections).

Identifying failure mode, identifying conditions by which the system cannot fulfill the goals of process.

Identifying causes of failure: identifying the causes can be done by historical failure, previous errors, related records, using potential failure, using experts experiences, using fault tree analysis (FTA), which is a strong tool to analyze complicated systems which has a top-down approach.

Determining the severity of the damage; damage severity identity's the seriousness of failure mode effect on purpose of the process and these is a direct relationship between failure mode effects in system performance and serenity of this therefore, a number between one (no risk) to ten (very important) is assigned. These numbers are used to prioritize the failure modes.

Identifying the number of failure. The number of failures is a type of rating or value which is estimated the probability of cause removing or controlling a number of causes or mechanisms can reduce the likelihood of errors. To determine the number of failure, date reliability or failure history can be used. The likelihood of accurance can be rated between one (minimum rate of incidence).to ten (maximum rate of incidence

Identifying the number of failure detectioning: the number of failure detection determines how much efficient activity is necessary for identifying and diagnosing the failure, is determines how much efficient the necessary activities is for identifying and diagnosing the failure. And in other woods the likelihood of detection of failure mode and preventive action is estimated. This number can be rated from one to ten.

Calculating risk priority number, the risk priority number (RPN) is calculated by multiplying number of severity and. Identification number and occurrence number. This number is the base for prioritizing the conditions of failure mode. When the RPN is high corrective actions should be taken.

Finally, after the above steps the following actions will be done:

1- Attempts to remove the failure modes has been made with regard to prioritization based on the number of risk 2- reducing downtime 3- Reduce the possibility risk of failure modes 4- Improved diagnostic methods 5- Recommend appropriate corrective actions After Determination Set points.

determining the reference points, the normal operating range, the maximum and minimum permissible processing parameters, pump, and the pump PFD simulation process diagram using information expert engineers and maintenance personnel and operating range of each of the processing parameters centrifugal pump center are shown the study. The range actually represents a fuzzy interpretation of each pump which processing parameters. Given the range of results and data, and the tools used neural network is the need for code input and output parameters of the network.

In order to validate the data collected from the pump, Log Sheet data were used, and for the past few years there have been cases where the neural network performance was evaluated. After the fuzzy preparation and Determination of the membership functions for each parameter of hydraulic and mechanical pumps.a set of daily data Flow Rate, Discharge Pressure, NPSHR, BHP, Efficiency, vibration and Temperature according to the Excel file are collected according to the Excel file (Figure 5).

H	G	F	E	D	C	B	A
Rule No.	Temperature	Vibration	Efficiency	BHP	NPSHR	Discharge Pressure	Flow Ra
1	198.4	11.3	66.2	53.2	4.29	3.91	276.3
0	183.3	8.72	60.5	50.84	3.67	4.17	327.8
0	173.5	10.1	60.1	60.41	4.83	3.87	313.7
0	181.6	4.64	59.5	46.29	4.32	3.79	308.7
0	183.8	5.37	66.4	55.01	3.25	4.24	220.5
0	181.6	4.84	66.7	59.56	3.97	4.12	225.7
1	196	12.2	66.4	55	3.88	3.9	311.2
0	182.5	9.42	60.6	51.07	3.37	4.58	426.4
0	188	7.94	67.2	57.01	3.82	5.27	318.9
1	184	12.9	70.2	51.73	3.5	4.07	311.3
0	180.2	9.49	61.8	50.49	3.5	4.7	309.9
1	186.8	12.2	67	54.24	3.88	3.7	261.5
0	173.4	8.75	66.4	43.35	3.83	4.54	414.2
0	175	7.83	66.6	56.12	4.07	3.9	278.5
0	178.4	7.99	67.6	53.92	3.4	4.75	303.6
0	180.3	7.82	54.9	48.5	3.46	4.47	224.6
1	210	11.9	68.5	54.92	4.7	4.56	240
0	177.6	10.1	65.5	45.15	3.72	4.66	389.7
0	183.2	8.84	66.5	41.75	3.49	4.51	373.3
0	185.7	8.12	64.1	61.09	4.14	4.59	364.4
0	184.9	3.78	55.1	51.04	3.68	4.62	330.8
0	166.5	10.8	64.5	46.52	3.92	4.59	278
0	176.4	8.58	63.9	55.55	4.24	4.54	419.4
0	179.8	9.44	61.6	49.46	3.77	4.65	314.2

Figure5. The data in the Excel file

Then comparing each of the parameter values range from simulation of a string of numbers was Extracted having special meaning. In this series of numbers, number 1 means very low, low, meaning the number 2, number 3 means normal, 4 and 5 would mean very high. For example, a string code [1 2 3 3 2 4 2] means very low flow rate, low Discharge pressure, Normal NPSHR and BHP, low efficiency, high vibration and low temperature, Table (1).

Table1. Table coded to operating parameters and process parameters

V	U	T	S	R	Q	P
5	4	3	2	1	No numerical strings	
Very high	high	Normal	low	Very low	Operating interval / Process parameters	
	509.4	370.5	324.2	0	Flow Rate	Hydraulic parameters
	550	509.3	370.4	324.1	) (	
5.34	4.73	4.57	0		Discharge Pressure	
5.7	5.33	4.72	4.56		) (	
	4.81	3.11	0		NPSHR	
	5.6	4.8	3.1		(m)	
	65.01	50.01	49.01	35	BHP	Mechanical parameters
	70	65	50	49	(kW)	
		66.1	56.1	0	Efficiency	
		73	66	56	(%)	
11.01	4.51	0			Vibration	
40	11	4.5			) (	
211	184	181	150		Temperature	
	210.9	183.9	180.9		) (	

The output of neural network code was needed to code the probable cause of failure which was extracted using the FMEA method. Thus, with default as it is observed that the rule number is extracted, for example, code (11) means" due to bearing failures, shaft rotates off axis to extract such an output, a need for coding in excel cells was required. Based on the input field previously described, Which is based on a series of conditions, extraction output code , is determined andbased on thatthe type of failure is recognized.
For training the neural network, part of the data for training, validation, and the other part of the network used to test After training in order to prevent the phenomenon Over fitting all evaluation parameters are extracted using 10 Fold Cross Validation [23.24]. And to assess the network after making an average of the accuracy parameters Precision, and Recall, that the Dead. In short the data from the test to evaluate the entries made in the study of Confusion matrix is used to test data. Evaluation parameters are calculated according to the following formula:

$$Accuracy = (TP + TN) / (TP + FP + TN + FN)$$
$$Precision = TP / (TP + FP)$$
$$Recall = TP / (TP + FN)$$

In this Study Positive means failure detection and Negative means (in order to verify) the Accuracy of the pump in the neural network. To be more familiar with this concept (Figure. 6) is used. This form of Recall and Precision provides a good explanation. This form is divided in two major parts [19]:

1. The safety of the pump (True Negatives + False Positives)
2. Deterioration of the pump (True Positives + False Negatives)

Therefore, in general, recall can be recognized as a ratio between correct diagnosis of the failure and all forms of failure, and precision is a ratio between correct diagnosis of failure and diagnosis of failure.

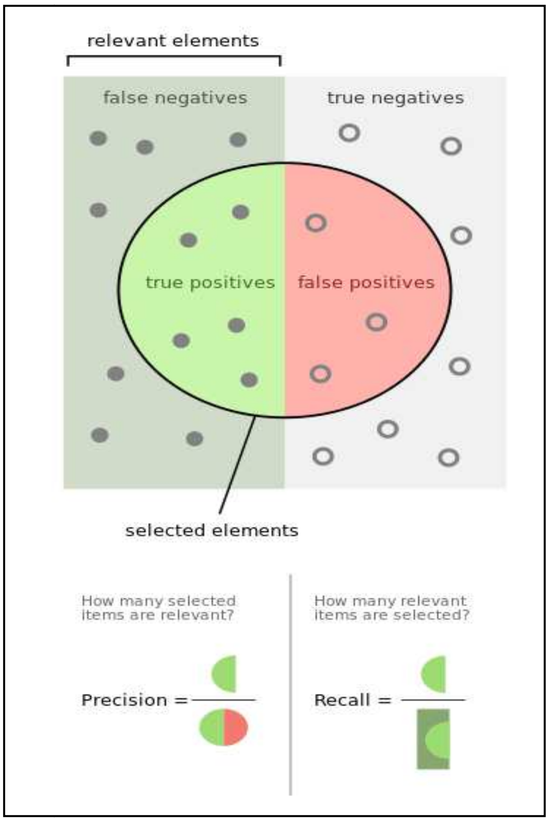

Figure6. The concept of parameters precision and recall From Wikipedia, the free encyclopedia

In this study, we used F1 score. The F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. It works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall. [21]:
The formula for F1 Score is 2*(Recall * Precision)/(Recall + Precision)
Comparisons of data distribution, the cost of false positive and false negative are shown in Table 2 [20, 22]:

Table2. Comparison of evaluation factors, putting them together

		Class distribution	
		Even	Uneven
Cost	FN cost more	Recall	Recall
	Same cost	Accuracy or F1 score	F1 Score
	FP cost more	Precision	Precision

4. Results

By completing the FMEA table, to find the impact of each of these failure modes and causes the hydraulic pump parameters, the simulation process knowledge extraction process in which the pump is activated, Certified engineers and maintenance personnel, the pump manufacturer's instructions, troubleshooting and to explore the impact of each of these failure modes and their causes on the parameters of mechanical pumps to extract knowledge from staff and expert engineers, maintenance, troubleshooting instructions manufacturer of pumps and pump references are made. This table is part of the specified conditions indicate failure. In this table, "D" means the reduction and "I" means increase. Since this study, the aim of applying FMEA, extracting linguistic rules and applying rules based on the results obtained in fuzzyExpert systems andExpert neural network.

Instead of calculating the risk priority number in the last column, the weight value, which is a number between zero and one is used, This number represents the weight (importance) of each rule in fuzzy expert systems. This number is based.on the rate of occurrence of defects, affecting the occurrence of a failure modes based on OREDA data failure, personal’s idea and Expert repairing and maintaining engineers. Based on obtained FMEA.74 linguistic rules are extracted including vibration, leakage, Spurious stop. An example of distruction vibration at law rate flow is shown in the Table (3).

Table3. Linguistic extraction rules based on FMEA, failure mode vibration and noise at low rates

Rule No.	If (Introduction)	Then (result)
Rule 1.	Flow Rate too low, low Discharge pressure, vibration and high temperature is too high	Pump suction pipe full of liquid is not enough
Rule 2.	Flow Rate too low, very low BHP, low efficiency, high vibration and high temperature	Discharge valve and pump has been convicted
Rule 3.	Flow Rate Low discharge pressure, high, very low BHP, efficiency is very low and very high vibration	Special high -speed vacuum pump is selected
Rule 4.	Low flow rate and BHP too high	Impeller selected by a factor of high altitude
Rule 5	very low flow rate, Discharge pressure, high, very low BHP, low efficiency, high vibration and high temperature	Discharge pump valve is closed without the path is open for drainage
Rule 6.	Flow rate low Discharge pressure, low, NPSHR high, low BHP, low efficiency, high vibration and high temperature	The pump is the input current lower than the minimum allowed
Rule 7.	very low flow rate, low Discharge pressure, NPSHR and normal BHP, low efficiency, high vibration and temperature is low	The intake valve opening and duct sealing is too much crime

10 years data pump in 4 shifts (14585 data) were collected and stored in an Excel file, with the help of simulation intervals in the table (1) and using the rules language 74 -fold (Table 2) and the formulation in Excel cell range numbered in order from 1 to 5 were coded based on rows of data using Excel conditional ordersThen each row is compared with simulated range and is defined according to languge rule, after that each row obtained a number ranging 1 to 74.

After reviewing the data collected from the stations surveyed, the highest failure rate is assigned to code number 77 including failure symptoms which is pump, vibration and noise.,in this case a cooding with the code sequence of [1 2 3 3 2 4 2] is Extracted, which are The very low- Flow Rate, low discharge pressure, high efficiency, low vibration and low temperature. According to a study conducted in such a situation, the intake valve over opened and duct sealing has mass.

The output of the neural network is needed for each of the modes of failure (14,585 data) and for situations that are more than 30 cases of failure. Neural network design, according to data from the error of the Table (4) states No. 2,10,14,23 and 25 were selected as the code output neural network to determine the cause of failure.

Table4. Table of Frequency failures

Pump Status	1	2	3	4	5	6	7	8	9	10	11	12	13
The number of cases	13031	98	1	1	14	4	1	3	4	126	2	2	20
Pump Status	14	15	16	17	18	19	20	21	22	23	24	25	
The number of cases	45	10	6	10	10	30	6	23	1	33	2	1102	

To identify the cause of the pump failure there are two fundamental issues: 1. The number of neurons in the hidden layer 2. Number of neural networks required for problem solving.
Regarding the first question, research, simulation and optimization analysis was conducted using F1 Score of 5 to 50 neurons in the hidden layer neurons, in the hidden layer 13 is the best performance of the results, there are shown in Table 5 and Figure 7.

Table5. Table on the number of neurons in the hidden layer

Part of the number of neurons in the hidden layer of software calculation results									
Counter i	6	9	16	17	20	23	25	26	45
The number of neurons	10	13	20	21	24	27	29	30	49
Fscore	0.8030	0.8127	0.8065	0.8019	0.8005	0.8112	0.8039	0.8069	0.8039

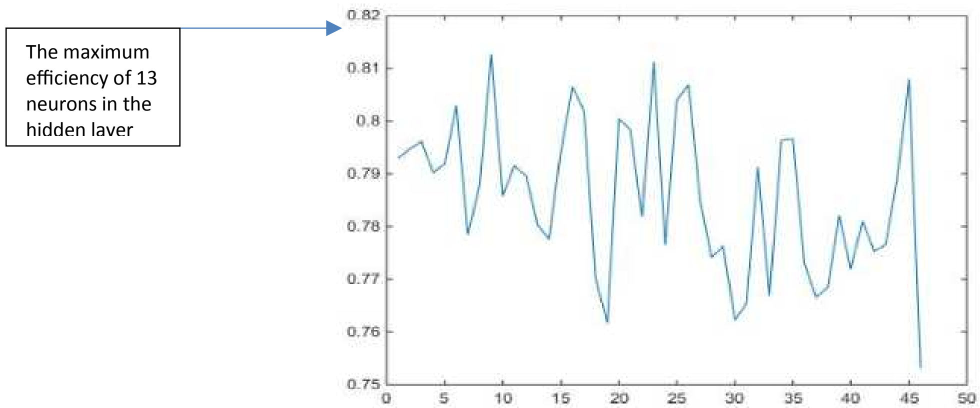

Figure7.Diagram of neurons in the hidden layer after calculations

To answer the second question were considered two states neural network. In the first case the neural network was built to detect pump trouble? Or not? Without having to look at what is wrong ? Because these neural networks are for two reasons: 1. To simplify the problem of state failure which is high and to get the job done. (2)That the information provided by the pump is broken or not? After the neural network recognize the pump is broken or healthy? ANN latter made for cases where there is a failure, And the failure to question 6 is therefore separate from our network, The first is to identify good or bad pump and 5 others for 5 of the failure of more than 30 cases have been training the neural network. In order to produce neural network, MLP neural network was Sigmund output function used. As stated, in training sets, which is used for neural network training, we use rows selected in such a way that data is selected randomly. This will cause data to be used for training homogeneous So put together a matrix of data obtained in order to prevent the phenomenon Overfitting all evaluation parameters are extracted using 10 Fold cross Validation [22,23]Each time a parts are trained, validated and tested. In this study, each neural network is produced 10 times and 10persent of each neural network is used for testing. Figure (8) shows the apart of neural network training and its geometry.

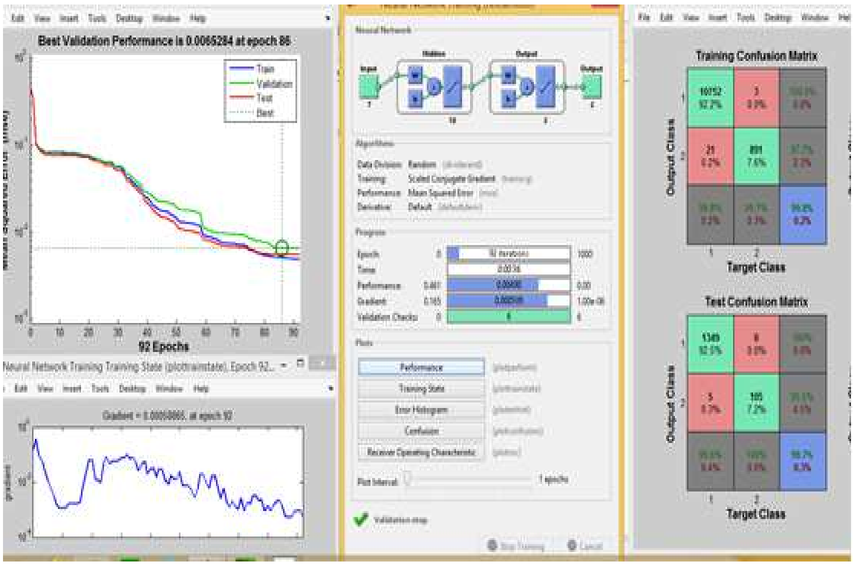

Figure8. The training and network performance charts

Failure modes corresponding to the 74's and the 24 kind of damage that they have data Writing code in MATLAB Each of the 24 states and the healthy state of the pump failure at the Table (6) are observed. The zero status in the original file shows the status of From 25 different pump states.

Table6. Table of correspondence in the file damage MATLAB and Excel files

Number of pump failure	0	1	2	5	6	9	10	11	14	15	19	20	24
Status of the table	1	2	3	4	5	6	7	8	9	10	11	12	13
Number of pump failure	27	29	30	33	37	41	42	45	46	47	55	77	
Status of the table	14	15	16	17	18	19	20	21	22	23	24	25	

After training the neural network to evaluate information stored in a variable, Then another matrix to test the accuracy of these three parameters (accuracy, precision and recall) data is stored. The first row in matrix is related to neural network fault detection and the right function of the pump and the next 5 rows (2-6) is related to fault in put [2,10,14,23,25]

After the training, part of the performance data measured by the test data, A sample of Confusion matrices of the parameters are calculated with 10 times (Figure 9). As can be seen, the test is 99.6 % accurate at identifying failure.

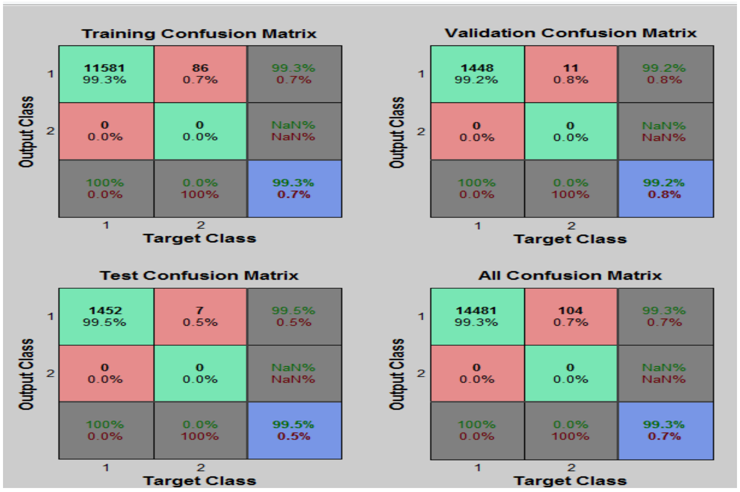

Figure9. Confusion matrix of neural network 10 times

Table7,when dealing with the gray areas are shown the number of failures which were less than 50 that have not obtained good accuracy in the neural network. The result is a neural network designed for failure 2, 10 and 25 with high accuracy and precision appropriate response capabilities. In general, the neural network has been trained for the damage that their data is closer to 100 and above works well.

Table7. Table of measuring the effectiveness of neural network

The total number of failures reported	Class failure	Accuracy	Precision	Recall
1554	Of all cases	0.96676	0.99354	0.68466
98	2	0.99746	0.83193	0.9
126	10	0.99493	0.63909	0.79375
45	14	0.99404	0.50552	0.40147
33	23	0.99034	0.37627	0.64724
1102	25	0.98328	0.97517	0.798

5. Conclusion and Summary

The results of this study shown the effects of different modes of failure on process parameters and mechanical hydraulic pump, it is recommended because the vibration parameters alone cannot determine the cause of failure in all cases, in addition to vibration parameters, the parameters flow rate, discharge pressure, NPSHR, BHP and temperature is monitored regularly and automatically. In this way faliure, not only can be detected at an early stage but fail to prevent human error and increased measurement accuracy.

The goal of future studies could include the following: the clustering of data collected in order to eliminate outlier and a neural network noise, and then build neural networks and analyzing the results and to compare them with the current system [25, 26]. Another study that can be done, such as the use of Radial Basis Function neural networks and evaluate the results [27].Another future studies may use KNN (k nearest neighbors) or SVM (Support Vector Machine) is because instead of trial and error to find the best network structure, it is possible with this method produced a neural network with the best performance [23,24].

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