An integrated qualitative trend analysis approach to identify process abnormalities: A case of oil export pumps in an offshore oil and gas production facility.

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Abstract:

Oil & gas production can be largely benefited by minimizing unwanted production losses. This can be done by effective identification of system anomalies and faults. In standard control systems these abnormalities can be observed as gradually deviating trends from the norms. Available tools for monitoring these trends, in some cases, may not be enough to reveal hidden faulty features. In order to interpret these changes accurately, measured data must be visualized as a combination of multiple sensor signals within a particular domain. This paper suggests an approach to effectively utilize integrated data from multiple sources, and defines a set of 12 fault features. The approach, in principle, encodes real plant data in the form of logical IF-THEN rules in Microsoft Excel. Confidence values are set based on these interpretations to differentiate between normal and abnormal conditions exhibited by the system. This is to provide an opportunity for the process and maintenance engineers to effectively identify the equipment's health based on the early identification of developing abnormalities.

Keywords: fault features, integrated trend monitoring, process control, centrifugal pumps

1. Introduction:

Industrial machinery involves high capital costs and its efficient use largely depends on having low operating and maintenance costs. In the offshore oil and gas industry, most machines are expected to work continuously 24/7, 365 days a year and are generally subjected to abruptly changing operating conditions. Analysis, monitoring and control of offshore industrial assets are often complicated and are affected by many factors such as uncertainties and/or incomplete understanding of process behavior. With successful implementation of Integrated Operations (IO) in the North Sea assets, the need for robust remote monitoring and surveillance has become quite evident [**10-11**]. To achieve these objectives, proactive machinery management, including predictive analytical techniques, is gaining huge attention that focuses on the ability to identify developing faults and problems at earlier stages. The information obtained from existing trend analysis programs can assist in uncovering hidden threats to the plant's integrity. The process of fault/abnormality detection in an industrial process includes detection of catastrophic events as well as the incidents (smaller faults). Proper detection of the incidents is of crucial interest as these can prevent the subsequent occurrence of more catastrophic events [**4**].

Production shutdown events taking place on the oil and gas platforms may result from a number of underlying causes. The root causes of these events are hidden mainly under various technical, human and organizational factors. Technical causes for shutdowns generally involve equipment failures that are known to play a major role in the overall plant integrity [**21-22**]. Equipment manufacturers generally provide each unit with integrated control systems and standard alarm levels. These standards comply with industrial standards and practices (e.g. API, ANSI recommended practices) that are applicable to a broad class of equipment of certain type. This also includes safe operating limits set by the manufacturer for variables such as ambient temperatures, pressures and working fluid properties (e.g. viscosity, sp. gravity etc.). The purpose is to ensure that the process remains under controllable limits at all times. However, in reality this might be different due to dynamically changing operating conditions. In the control systems, threshold limits are associated with alarms/alerts to warn the operator when the process experiences any abnormality. Generally, the threshold limits are set too wide and therefore in some cases these may be a poor indicator of the system's condition (Figure 1).

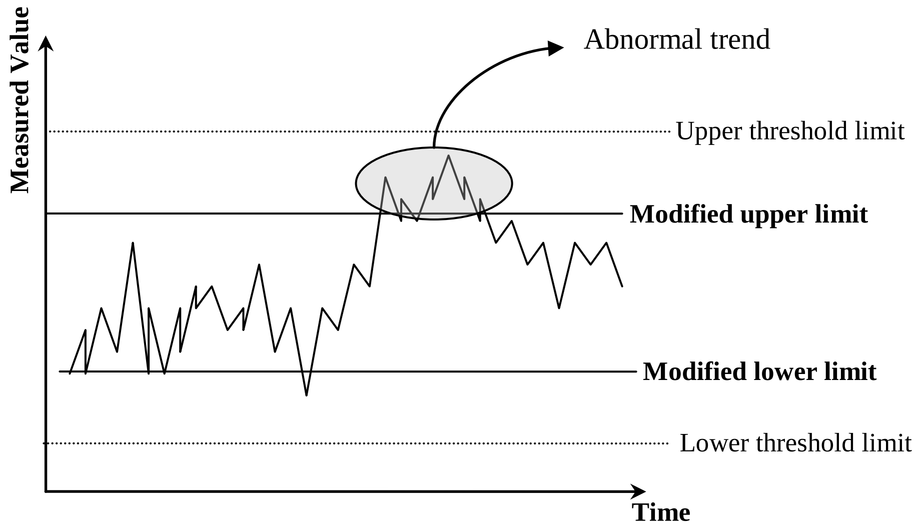


Fig. 1 Process monitoring with standard statistical limits

Figure 1 presents how an abnormality can remain undetected under normal operating conditions (shown as encircled part in the figure). These variations may represent symptoms of an upcoming fault and, if interpreted properly, these can provide vital information about the condition of the operating unit. Some examples of commonly known fault symptoms include excessive vibrations, elevated noise levels and higher thermal profile etc. In some cases, poor quality and the ambiguous nature of these symptoms have a tendency to create misconceptions for system operators to overlook or misinterpret these indications. This may also present a tedious job for data analysts and experts to keep track of these seemingly '*make-no-sense or negligible'* changes that are often to be interpreted as '*harmless or no-threat'*.

The approach proposed in this context is based on identifying and interpreting symptoms that may develop into potential unwanted consequences. To demonstrate this, a user interface is developed in Microsoft Excel that uses multiple sensor signal data (time-series) from oil exporting pumps located on an offshore oil and gas production facility. Pre-identified failure modes are coded in the form of logical IF-THEN equations. The results from the analysis can be a useful input for efficient decision-making that can consequently reduce the unwanted outcomes.

2. Literature Review:

Trend analysis is a useful approach to represent numerical data in a qualitative or semi-qualitative way. The main objective is to convert online data into useful knowledge to support decisions made by the operators [**6**]. The process of fault diagnosis is broadly classified in terms of model-based and history-based methods. These include qualitative and quantitative methods to describe the interaction between various process variables. Qualitative methods mainly comprise of qualitative trend analysis (QTA) techniques, whereas quantitative methods make use of advanced statistical and artificial intelligence techniques such as neural networks [**7**]. In real life situations, equipments/processes are subjected to extreme conditions and therefore are more vulnerable to faults.

Condition monitoring and fault diagnosis has been an exploratory paradigm for many researchers. To improve the reliability and availability of the equipment, computer-aided maintenance techniques have been established considerably well during the past two decades [**20, 28**]. The purpose is to monitor equipment condition based on dynamically changing operating conditions and to plan maintenance tasks in order to avoid critical malfunctions. Several researches in the nineties attempted to integrate condition monitoring techniques into specialized maintenance systems [**12, 26, 3, 23**]. These techniques continuously monitor the mechanical condition of the equipment and, in some cases, these can predict potential failures [**25-27**]. However, most of the condition monitoring (CM) techniques need human expertise to identify and diagnose faulty conditions.

In today's world, increased automation and computing power has resulted in large amount of available data. Most process diagnosis and monitoring techniques use trends that are a hierarchical representation of signals. Dynamic trend analysis, also known as qualitative trend analysis (QTA), is one of the preferred techniques to extract useful information from measured signals in monitoring the state of a process. In qualitative terms, similar (different) events result in qualitatively similar (different) trends [**13-14**]. This means that unwanted events can be qualitatively represented by carefully analyzing the respective trends.

Gabbar et al. [**9**] proposed a technique based on data trend analysis using MATLAB as a tool for computations. They conducted an experimental study constructing trend signatures based on regression method and comparing trends of normal and abnormal conditions. In large maintenance databases, data mining techniques such as neural networks, fuzzy logic and statistical methods can be effectively employed to explore the trends [**29**]. Priorier and Meech [**19**] introduced the concept of intelligent alarms based on fuzzy logic and rules of thumb to analyze time-series process data. To govern the state of the process, they coded the alarms as IF-THEN rules. In short, various applications of trend analysis have shown that valuable information extracted from the plotted trends can be effectively used in improved surveillance and optimization tasks [**15-16, 8**].

In the cited literature, the authors presented both qualitative and quantitative methods to diagnose process faults and abnormalities. For instance, see **13, 19, 9**. It will be shown here that the use of qualitative trends can provide useful results in complex processes. The work describes how faulty patterns can be expressed directly from real plant data that can provide a basis for identification of the developing faults. The user-interface developed in Excel generates automated early warning levels based on a logical combination of the fault features. Collected data from oil export pumps from an offshore oil and gas production facility is used to test the proposed strategy that showed promising results.

3. Proposed technique for identifying abnormal trends:

The proposed strategy is based on *cause-effect* reasoning about a system's behavior. Fault trees are among the most popular techniques in this regard [**7**]. The proposed approach used failure modes and represented them in a more user-friendly way. Data from the oil and gas production platform is collected from multiple sources. The data format can be characterized as qualitative and/or quantitative and static and/or dynamic form. Fault detection is usually performed by monitoring real time plant data and extracting features from input process and/or equipment variables. These variables need to be classified as normal or abnormal which identifies the condition of the system. The approach discussed in this section used time-series quantitative data from multiple sources imported into a Microsoft Excel spreadsheet as a database of normal and abnormal features. Figure 2 shows schematically how the proposed strategy fits in relation to the given operational scenario at the facility.

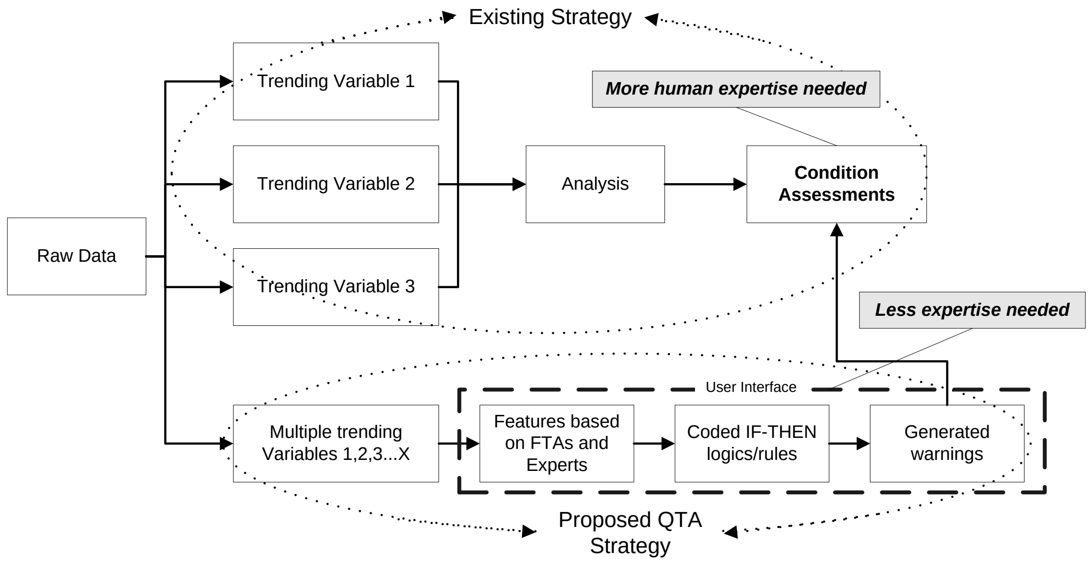


Fig. 2 Existing and proposed QTA strategy

As aforementioned, a conventional trend analysis program demands more involvement from human experts. This relies heavily on human interpretation and perceptions. The proposed technique used experts' opinion in defining the feature of critical faults. Once these are coded in the user interface, they provide a way to detect system anomalies in a more *automated* way.

Trend analysis at the facility under study is based on plotted trends and analyzing these individually to assess the condition of the operating unit. In contrast to this, the proposed strategy used simultaneous trending of variables where major failure modes are represented as fault features. Extensive analysis of vendor data, historical shutdown data and domain experts' opinion was included in defining the critical failure modes of operating pumps at the facility. These failure modes were coded in the form of IF-THEN logical rules in the user interface developed in Excel that was specially designed to perform the task. Warnings levels were set and the alerts were generated when there were abnormalities seen in the process.

Archive data from an offshore production platform was collected at a regular interval of 10 minutes. The interval selection criterion was based on experts' opinion as it normalized the abrupt changes due to surging operating conditions. However, it was also realized that minimizing this interval could greatly improve the quality and reliability of generated warning levels.

Fault features in this context are encoded in the form of condition-action pair, e.g.

IF *this condition occurs*

AND *(contributing variables above or below specified limits)*

THEN *possible failure event is "fault A"*

e.g. to identify change in liquid viscosity in a running pump, the logic will be

IF "*increased motor temperature*" AND "*higher Power demands*" AND "*reduced capacity*" AND "*reduced fluid temperature*" AND "*reduced discharge pressures*" THEN "**High sp. gravity**" ELSE "***OK***"

Similarly, logic for deviation of a pump from its *Best Efficiency Point* (BEP) can be given as:

IF “*higher inlet temperature*” AND “*higher Inlet Pressure*” AND “*higher flow variations*” AND “*higher motor speed*” AND “*shaft deflections*” THEN “**Deviation from BEP**” ELSE “***OK***”

A major limitation in defining these rules was the data availability. In our case study, vibration data, which could be used as a critical indicator for some faults, was not available. As an example, insufficient discharge pressure, insufficient capacity and excessive power demands coupled with high vibration levels can be regarded as an indication of internal wear of the pump. The most simple and straightforward qualitative method of detecting deviations consists of a threshold test of a feature. The threshold limits are set for each variable to ensure that the process remains under control. Breach of these limits initiates alerts/alarms in the standard control systems. Generally, these threshold limits have wide ranges to prevent the control systems from overloaded warnings/alerts. In the logical equations, threshold limits were redefined statistically for normal and faulty conditions. These modified limits were then used in developing the user interface to assess the system’s health. A confidence value (CV) is set for each feature that categorizes corresponding trends as normal or abnormal. The CV of “1” and “0” represent normal and abnormal conditions respectively. These warnings indicate slowly developing problems that may or may not cause serious damage to the equipment but also reflect the need for a detailed check of the system by operators and experts.

4. Example of oil export pumps:

4.1 System description

Sensor data from an oil export pump located on an offshore oil and gas production facility is collected to test the defined fault logic. Centrifugal pumps are widely used in various industrial applications. These are classified as rotodynamic type of pumps in which dynamic pressure is developed that enables lifting of liquids from a lower level to a higher level. Centrifugal pumps are highly susceptible to process variations and therefore the dominant reasons for centrifugal pump failures are usually process related [**5, 17**].

The offshore production facility under study uses 3 parallel connected centrifugal type pumps to export the oil to onshore. Two of these pumps (named here as A and B) are driven by variable speed drive (VSD) motors, whereas the third pump (named as C) has a fixed speed drive (FSD) motor. Figure 3 shows the selected system boundary and the distribution of sensors’ signals within the domain. Collected time-series data from sensors is displayed in the form of trends that are made available to onshore experts.

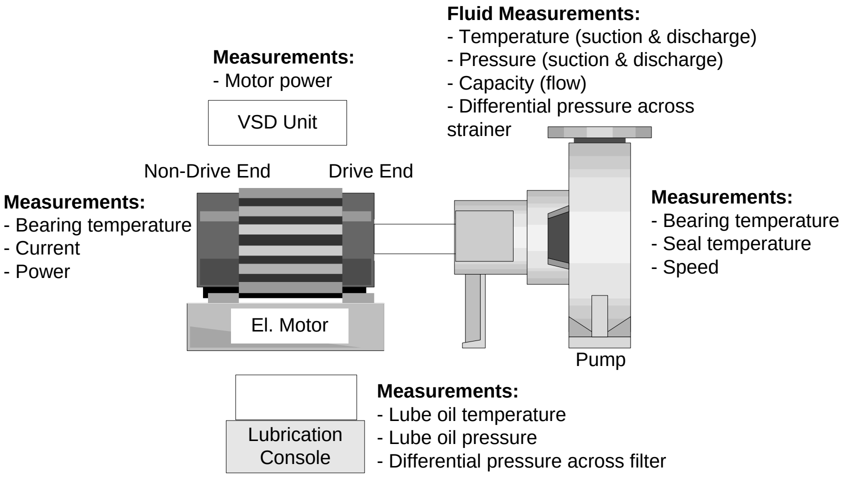


Fig. 3 Experimental measurement points for trend analysis

The export oil pump system consists of electric driving motor, pump skid and lube oil console. Figure 3 shows measurement locations (also referred to as tags in this context) within the selected pump system. Due to an extensive number of tags associated with this system, only those were selected that had a larger effect on pump performance. The data sources included critical performance indicators from:

- Data for condition monitoring (e.g. bearing and seal temperature, etc.)
- Process variables (e.g. inlet flow, capacity, inlet temperature etc.)
- Auxiliary systems variables (e.g. lube oil temperature, lube oil pressure etc.)
- Other data sources (environmental data, e.g. noise etc.)

The offshore facility had an annual maintenance shutdown in 2007 and therefore the data used to develop the interface was considered as healthy and fault-free. Based on the fault tree analysis, Figure 4 shows how the 12 defined faults are associated with multiple data sources that included process, equipment condition monitoring and auxiliary data etc.

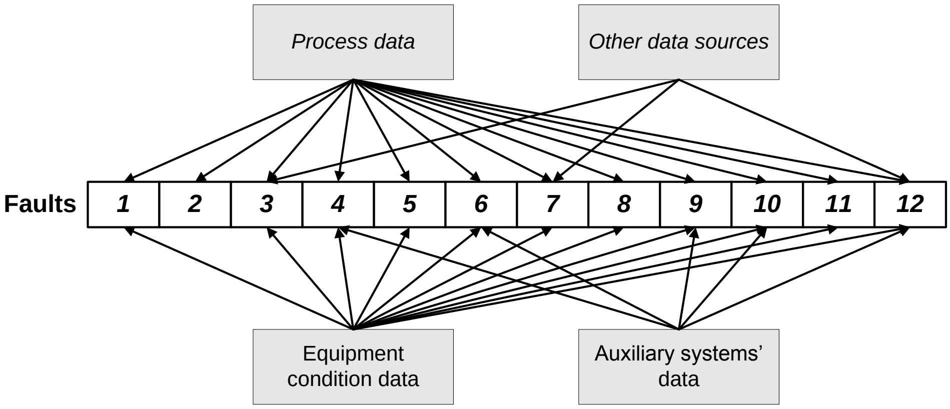


Fig. 4 Data-Event relationships

The variables in these data sources used modified threshold limits to recognize the abnormality in measured value. The control value (CV) is used as an indicator of state of the operation. According to Al-Najjar and Alsyouf [**1**], faults may develop due to many causes represented by large standard deviation.

Based on the above defined approach, a total of 12 critical faults was formulated. Table 1 gives an overview of the defined fault features along with the displayed indications from the Excel-interface. This generated an alert in the form of CV of either 1 or 0 indicating when it detected the particular faulty pattern.

Table 1: Defined critical faults and their indications

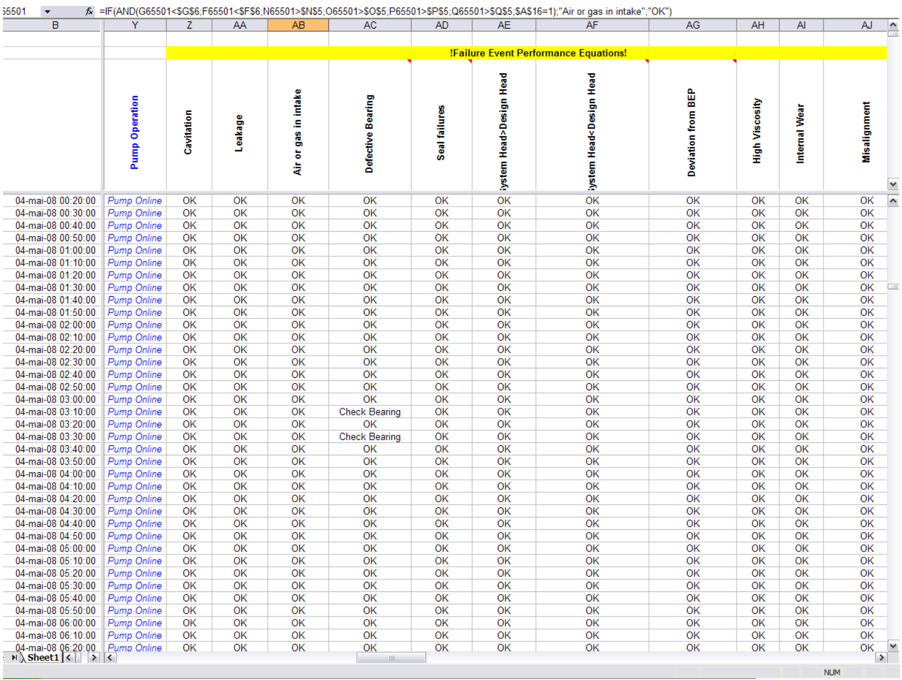
Fault No.	***Description***	***Displayed Indications***	***CV***
1	Cavitation	*"Onset of Cavitation"*	"1" or "0"
2	Leakage	*"Check for leakage"*	"1" or "0"
3	Air/gas in intake	*"Air or gas in suction"*	"1" or "0"
4	Defective bearing	*"Check bearing"*	"1" or "0"
5	Seal failures	*"Check seals"*	"1" or "0"
6	System Head > Design head	*"System head increasing"*	"1" or "0"
7	System Head < Design head	*"System head decreasing"*	"1" or "0"
8	Deviation from BEP	*"Deviating from BEP"*	"1" or "0"

6	Sp. Gravity too high	*"High sp. Gravity"*	"1" or "0"
10	Viscosity too high	*"High liquid viscosity"*	"1" or "0"
11	Internal Wear	*"Check for internal wear"*	"1" or "0"
12	Misalignment	*"Check alignment"*	"1" or "0"

A brief summary of the results from testing these logics for real plant data from operating pumps is described in the next section.

5. Results and Discussions:

The approach presented here has a huge potential for revealing early indications of faults that can provide a knowledge base for early decision-making in order to avoid potential shutdown. A screenshot of the Excel-based interface developed to identify and monitor multiple trends is shown in Figure 5. The coded fault logics are based on the information from sensor data embedded in the same spreadsheet.



55501 =IF(AND(G65501<G6;F65501<F6;N65501>N5;O65501>O5;P65501>P5;Q65501>Q5;A16=1);"Air or gas in intake";"OK")

B	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ
		!Failure Event Performance Equations!										
	Pump Operation	Cavitation	Leakage	Air or gas in intake	Defective Bearing	Seal failures	ystem Head>Design Head	ystem Head<Design Head	Deviation from BEP	High Viscosity	Internal Wear	Misalignment
04-mai-08 00:20:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 00:30:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 00:40:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 00:50:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 01:00:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 01:10:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 01:20:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 01:30:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 01:40:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 01:50:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 02:00:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 02:10:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 02:20:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 02:30:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 02:40:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 02:50:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 03:00:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 03:10:00	Pump Online	OK	OK	OK	Check Bearing	OK	OK	OK	OK	OK	OK	OK
04-mai-08 03:20:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 03:30:00	Pump Online	OK	OK	OK	Check Bearing	OK	OK	OK	OK	OK	OK	OK
04-mai-08 03:40:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 03:50:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 04:00:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 04:10:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 04:20:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 04:30:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 04:40:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 04:50:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 05:00:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 05:10:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 05:20:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 05:30:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 05:40:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 05:50:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 06:00:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 06:10:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
04-mai-08 06:20:00	Pump Online	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK

Sheet1

Fig. 5 Screenshot of Excel-based inference engine

5.1 Identification of "normal" and "abnormal" operational parameters

Key parameters of the pumping operation included several variables such as flow, inlet/outlet pressures, seal and bearing temperatures, current and motor temperature etc. The threshold limits of these variables were compared with existing limits in the control systems. Fault-free data was selected to recognize features of a normal operation. These settings were taken as a baseline to represent normal operating conditions. The selected baseline limits for the installed pumps are shown in Table 2.

Table 2: Modified Operating limits for Export Pumps

	Pump A and B		Pump C	
Variables	**Existing limits**	**Baseline limits**	**Existing limits**	**Baseline limits**
Flow (m^3/h)	0-3200	850-1685	0-3000	736-2171

Inlet Press (BarG)	8-28	17-19	7-30	16-19
Motor temp. (°C)	2-72	24-48	3-170	68-102

Similar operating ranges for other available variables were defined including bearing temperatures, speed, power demands etc. Relatively higher limits were set for pump C as this is a fixed speed pump operating at higher loads than the other pumps.

5.2 Statistical correlation

Sensor signal data from multiple sources was also checked for statistical relationships. Linear and non-linear relationships were found among different variables using simple and multiple regression models. In descriptive statistical analysis, the correlation coefficient indicates the strength and direction of the linear relationship between two random variables [**2**]. A correlation coefficient between ± 1 measures the degree to which two variables are linearly related. A perfect linear relationship between positive slopes of two variables has a correlation coefficient of 1. For a non-linear relationship other techniques are suggested that may include Neural Networks, Fuzzy logic or hybrid systems (referred to as extension of the current work). Results from the linear statistical correlation are summarized in Figure 6. It shows the strength of the linear statistical relationship between different sensors' signal data.

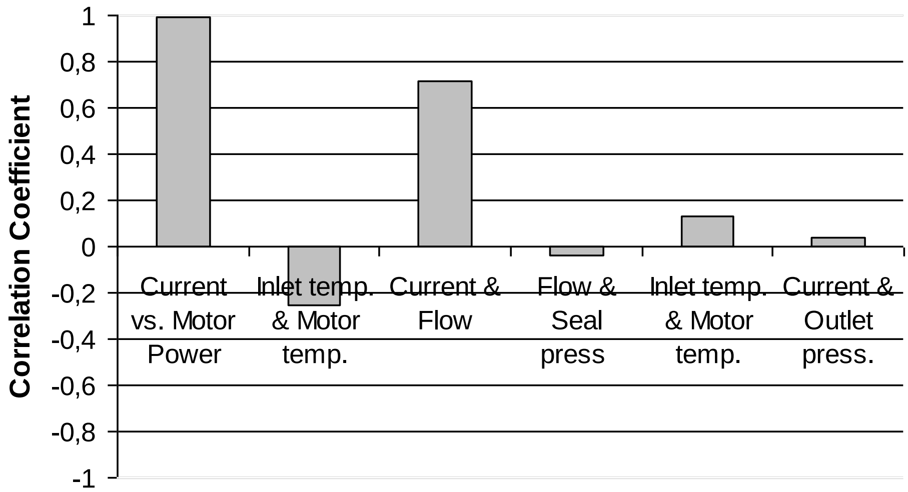


Fig. 6 Linear correlation based on correlation coefficient

A strong linear correlation was found within some variables (e.g. current-flow and current-motor power), whereas a correlation coefficient of 0 or near zero represented either the variables were not related or there exists a non-linear relationship between them. Such correlation was important to understand the mutual dependencies of these sensors. This dependency helped reveal hidden associations among different sensors within the selected domain.

5.3 Symptoms of developing abnormalities

Logical equations formulated in Excel spreadsheets displayed faulty features in the form of control values (CVs). The Equations were formulated for all 12 faulty features, and operational data from 3 months (July-September 2008) was used to test the logic. These datasets showed significant indications of faulty features 3, 4 and 8. When checked against the existing control systems, no alerts/alarms were initiated as none of the variables exceeded its threshold limit. Figure 7 shows indications of captured probable faults in form of a CV during normal operation of pumps in this 3 month time period. This was acknowledged by the domain experts as providing a strong base for the early identification of developing probable faults in the pumps from collective trend monitoring. In Figure 7, a CV dropping to 0 symbolically represents detected faults as interpreted in the user interface.

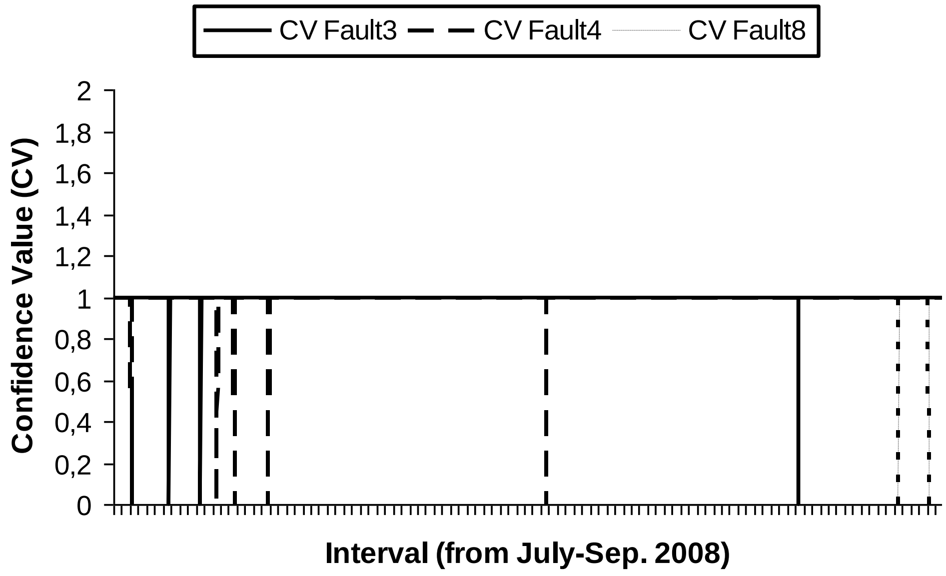


Fig. 7 Symptoms of faults in real-plant data

Conclusions:

Knowledge discovery and data mining is a very dynamic research and development area that is reaching maturity. An excellent survey of knowledge discovery and data mining process models is given in [**30**]. The approach presented in this paper can serve as a common set of criteria where different techniques can be evaluated and compared. Through this paper, we proposed an approach that aims to track fault symptoms and anomalies in a process that may lead to fault. Based on QTA, a brief discussion on the development of multiple-trend based analysis program has been presented. A user interface was developed in Excel that contained coded fault symptoms in the form of logical IF-THEN and IF-AND-THEN conditional statements. Three months' data from centrifugal type oil export pumps on an offshore oil and gas production facility was utilized to check the validity of these equations. The user interface can identify faulty patterns on earlier stages than the standard control systems and can generate warnings when any abnormality is observed in the data. The model successfully captured indications of some defined faults that generated multiple warnings during 3 months' continuous operation of one of the pumps. In existing control systems, these changes did not trigger any alert. These new warning levels are acknowledged by domain experts.

Future work and directions:

This work has been tested for archived data and has a great potential to be tested for real-time online data. The work presented here provides a strong base for advanced technologies based on AI tools such as Fuzzy logics, Neural Networks, Genetic Algorithms etc. that can be successfully applied as an extension to this work. In this regard, Zhang and Morris [**31**] presented an excellent extension of the work using fuzzy neural network. A more recent work towards such knowledge based systems in process control and fault identification can be found in [**32-34**].

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