Managing hidden system threats for higher production regularity using intelligent technological solutions: A case study

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Abstract: Identification and interpretation of hidden system threats on complex oil and gas production platforms has always been a challenge. These threats may gradually develop into failures/faults resulting in system shutdowns or eventually loss/reduction of production. Oil and gas industry is willing to test new technologies in managing uninterrupted, higher production regularity. In response to these challenges, a research project was initiated involving a leading oil company in Norway. A systematic investigative approach was adopted which incorporates domain experts' opinion and multiple information resources/databases. The paper attempts neural network modelling of a critical production loss-related scenario, based on real plant data from an offshore production facility. Analytical results captured symptoms of suboptimal performance from compressors installed in the gas compression system. This methodology could give plant operators an opportunity to early identify system's anomalies. As a result, unwanted shutdowns can be avoided, consequently improving overall plant's efficiency and productivity.

Keywords: artificial neural networks; ANNs; compressor suboptimal performance, production regularity.

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1 Introduction

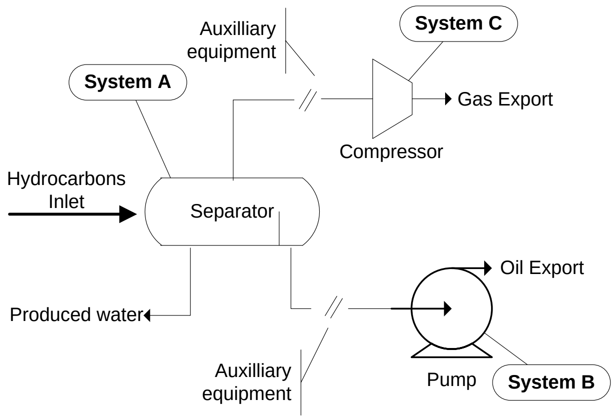
Assurance of oil and gas flow with minimal interruptions has always been a big challenge to the oil and gas industry. Despite all efforts, production shutdowns do occur due to different reasons. The underlying root causes of these undesirable events are sometimes identified through extensive investigations, but in some cases they remain completely unknown. Lessons from past experiences significantly contribute to continuously improving existing controls and safety barriers. These provide a firm base to lay out suitable strategies to hinder or mitigate the occurrence of such incidents. The available options may include improving human performance, increasing equipment reliability and availability, or optimizing existing work practices (Raza and Liyanage 2007).

Unplanned downtime of the equipment plays a crucial role in large petrochemical plants (Tordinov, 2005). One way to reduce the probability of such unplanned events is by improving the reliability and availability of the installed equipment. Equipment availability and reliability have a major impact on the overall plant economy (Boyce, 2003). Particularly in the oil production sector, the unplanned outages pose considerable economical challenges and may result in loss of earning opportunities. Asset management practices in bigger organizations seem to be quite conventional. Thus, there is huge technological need for testing and implementing smarter analytical techniques that can improve overall uptime of the equipment by the early identification and interpretation of abnormalities.

Patricio et al., (1997) concluded that the disturbances that produce oil and gas load disconnection or other emergency situations have to be localized as quickly as possible. In order to restore normal oil and gas production, localizing a disturbance is extremely important that starts with the process plant reconfiguration. This also requires precise and accurate identification of the developing disturbance.

In the oil and gas production process, a mass flow of hydrocarbons (comprising of water, CO_2, H_2S, sand, mud etc.) from oil wells is brought to separators where these are separated into oil, gas and water streams. Oil and gas are exported through pipelines, whereas water is recycled or fed back to the sea. Figure 1 schematically shows the main components of the oil and gas production process. In the figure, systems A, B and C represent the target areas. The figure shows the separation system for oil/gas/water (A), the export system for crude oil (B), and the produced gas compression system (C) respectively. Detailed selection criteria for these systems are discussed in Raza and Liyanage (2007 & 2008). In this paper we analyzed systems A and C, whereas system B is separately covered in Raza and Liyanage (2009).

Figure 1 A schematic oil and gas process diagram



Good separation of oil/gas/water is required not only for improved product quality but also to minimize any possible disturbances in the equipment or its neighboring systems. The occurrence of these peculiar changes can exhibit abnormal data patterns in the system. These anomalies can be efficiently used for early fault diagnosis and prognosis. The challenge here lies in precisely identifying these random changes and interpreting them into useful information.

Hooimeijer and Azmi (2006) emphasized that the fault identification from real-time data alone is not enough to capture system abnormalities. Engineers and analysts should utilize methods to analyze online data for the quick and early detection of probable faults. Alternatively, Tordinov (2005) concluded that in reliability studies, removing critical failure modes at the design stage is considerably cheaper than removing these at the manufacturing or operational stage. However, all failures cannot be removed cost-effectively. In case of an operating unit, failure modes can be identified from different patterns exhibited by the data. Several authors have proposed different approaches within the domain of fault identification. For instance, Mearns and Flin (1995), Khan et al. (2002), Khan and Amyotte (2002) and Oke et al. (2005) focused on offshore safety and risk assessments when dealing with critical events from petrochemical plants.

Recently, Kovalev et al. (2003) focused on large oil and gas production losses caused by surging flow conditions in the flow lines. Moreover, oil and gas processes suffer greatly from scaling (depositions due to corrosion) and slugging (mud/solids) in the vessels, pipelines and valves etc. Slugging, in particular, causes high-level trips in separator vessels that can disturb the fluid/gas equilibrium, thus resulting in instable operational conditions. This was among one of the most frequently recurring problems as reported in the corporate databases of the existing plant.

Some authors in the cited literature addressed these problems using artificial intelligence (AI) techniques. Recently, Liao et al. (2008) used fuzzy logic based control for the petroleum separation process. Fuzzy logic controller (FLC) is a proven technology for dealing with uncertain systems that has been applied in many industrial domains. Godhavn et al. (2005), on the other hand, suppressed slug generation by effectively controlling topside choke. In the field of artificial intelligence (AI), neural networks have widely been developed for several industrial tasks including prediction and forecasting, monitoring and diagnosis, classification tasks, signal processing and pattern recognition etc. (Cook et Al., 200;, Mohaghegh, 2000; Zangl & Oberwinkler, 2004). As Haykin (1999) notes, it has emerged as a powerful tool in various fields of engineering endeavors.

To assure uninterrupted production of oil and gas, field engineers and experts continuously improve safeguards to avoid any unnecessary drop in pressure or flow levels in the process. Warnings generated by the process control and safety systems play a critical role in improving the overall safety and reliability of the systems. These controls ensure that the facility is operated within the design window at all times. A stable operation results in cost-effective operational benefits such as fewer shutdowns, lower breakdown maintenance, less flaring, lower fuel consumptions etc. In reality, however, perfectly stable processes are rarely maintained due to dynamically changing operating conditions.

In this paper, realizing the challenges, we emphasized on developing neural network models based on critical indicators selected from real plant data to identify symptoms of suboptimal performance. The basis framework of such a system is discussed in details by Raza and Liyanage (2008). One of the main focuses of our study is an attempt to address discrepancies found between the theory and the practice. Qualitative and quantitative evidence are included and the study attempts to answer the following questions:

- What are the early indicators of suboptimal performance in the process understudy?
- How can these be identified within seemingly normal operating conditions?
- Which systems/sub-systems are more vulnerable within the domain of interest?

2 Methods

The aim of the study was to systematically model the collected data that can provide a sound base for detecting general system abnormalities. A case study was conducted involving a major Oil and Gas (O&G) operator in Norway in an attempt to answer the questions highlighted in this paper. According to Yin (2003), case study methods allow investigators to retain holistic and meaningful characteristics of real-life events. He stated that major case study strategies can be distinguished by the type of research questions raised about the phenomenon under study. In order to strengthen the study, David (2006) presented strong arguments on using advanced mixed methods in research designs that include analysis of a collection of quantitative and qualitative data. Giere (1997) proposed a methodology to collect real world data through observations and develop a model that fits the problem scenario. The purpose is that the developed model can make predictions based on the specific reasoning and calculations. These predictions must be verified against the real data to agree or disagree with the proposed objectives.

Collected qualitative data included inputs from historical production shutdown databases, vendor data, existing process control strategies, and brief interviews with offshore/onshore experts. Quantitative data was collected in the form of time-series sensors' measurements. Qualitative data was used to develop quantitative analysis. In Steckler *et al.* (1992), this approach is among the four alternative procedures for combining qualitative and quantitative research methods.

Following the essence of the principal methodologies given in this context, the collected information from multiple sources was analyzed to look for common themes and trends. The process of qualitative analysis was based on thematic analysis, whereas advanced statistical and data-handling tools were used to perform quantitative analysis (Neuman, 2006; Gill and Johnson, 2002). According to O'Leary (2004), a good methodological design addresses the raised questions, limited within the domain of interest, in a practicable and effective manner.

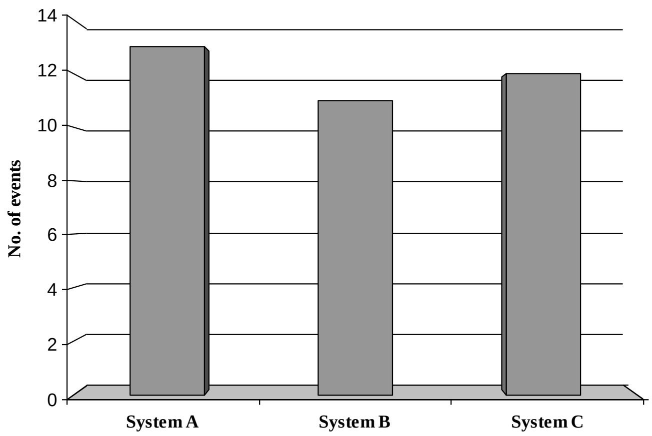
3 Findings and results

Findings of the case study are summarized in two separate sections. The first section covers the qualitative information and findings based on the databases and domain experts' opinion. The second part explains the modeling of quantitative data supported by qualitative findings from a specific case, in an attempt to answer the core questions.

3.1 Database findings

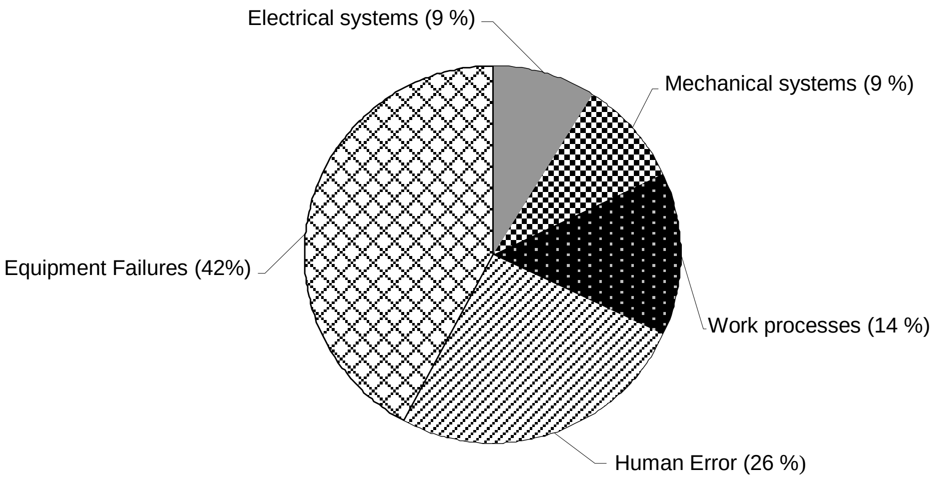
Investigations were started by looking into the available data and information from production loss databases, operational reports, well-test databases and corporate management databases etc. Initial risk assessments based on frequency and impact analysis highlighted the top most critical systems, as discussed in Raza and Liyanage (2007). Figure 2 shows the critical systems with the number of events that led to production shutdowns in the past.

Figure 2 Critical systems ranking (from 2004-2008 corporate database)



Root-cause based classification of these events is addressed in Raza and Liyanage (2007) which highlighted major failure modes within these systems. Based on this classification, Figure 3 reveals the underlying root causes of these events on the existing facility.

Figure 3 Root cause categories of production loss events (2004-2008)



This showed a higher contribution from equipment failures (up to 42%) which severely affected oil production in the past. The pie chart presented in Figure 3 is based on the percentage of total unplanned losses reported in corporate databases.

3.2 Domain experts' point of view

As the investigations proceeded, several meetings with domain experts were arranged to understand the practical issues related to these events. Active participation from onshore and offshore experts was ensured to recognize technological challenges in order to select a suitable solution strategy. Based on these discussions and arguments, a summary of practical issues concerning these losses is presented in Table 1.

Table 1 Practical issues related to production loss events

Equipments	*Practical issues*
Gas compressors Pumps Separators	- Handling and prioritizing of alarms/alerts - Failures due to neighboring systems in the process - Mechanical failure - Surveillance and control - Human Error - Process related failures - Maintenance errors

The issues summarized in Table 1 represent vast domains and needed further refining to prioritize the key issues. This led the attention towards the existing surveillance and control strategies of installed systems/equipments which emerged as the main target area. In this respect, an offshore visit was carried out to further discuss these issues with field engineers and front-line operators. Table 2 briefly summarizes some important issues that were surfaced in this respect.

Table 2 Key target areas and technological issues

Categories	*Technological issues*
Export pumps	- Less frequent - high impact events - Heavily relying on conventional condition monitoring methods - Understanding relationship between process variables and equipment wear and tear
Flash Gas Compressors	- Highly susceptible to process variations, surges - Third party shutdowns
Separators	- Process-related disturbances - Experience-based reasoning for handling process variations

Besides these, several other common issues were recognized as an important part of dealing with such complex problems. Some of these were:

- Sensors/data acquisition failures
- Lack of collaboration/communication among databases
- Auxiliary system failures (e.g. failures due to cooling, air supply, lubrication systems etc.)

However, in this paper, these issues were not taken into consideration. Experts formally involved in investigations have an important role in the decision-making process since this brings both experience and available information together to study a particular event. These decisions involve certain expectations about the future actions, such as recommending a scheduled maintenance etc. In past reported events, the responsive decisions included large amount of uncertainty. This was reflected as ambiguities and doubts in identifying and locating the causes of the failures. In some cases, the root causes remained completely unidentified due to the complex nature of the event. This uncertainty also justified the need for a more robust, reliable monitoring that can provide valuable information based on the initiating incidents. Uncertainty factors indicated in the past shutdown events are given in Table 3. This uncertainty factor is based on the percentage of total unplanned failures from the identified systems.

Table 3 Uncertainty in past events

Systems (2003-2008)	*Uncertainty factor*
Pumps	70%
Compressors	55%
Separation system	45%

Analytical results from expert opinion, databases, field studies and personal inference clearly identified the improvement opportunities. Artificial Neural Network (ANN) was used as a tool to develop a generalized model of the process using real plant data from separation vessels and compressors. The modeling results are discussed in more detail in the next sections.

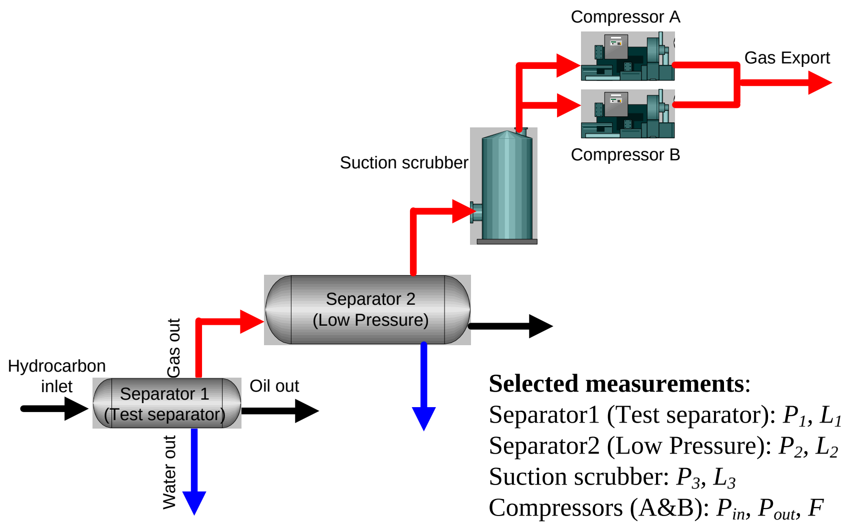
3.3 Modeling based on process-data

Case study example

Data from a recurring event was collected, pre-processed and analyzed prior to start with the modeling phase. Raw data was checked for correlations, missing values, outliers and noise etc. The correlation matrix showed highly non-linear complex interrelationships. The data was then carefully selected in a manner to include all operating conditions that could influence the model output. The neural network approach was adopted in contrast to the approaches described in Liao *et al.* (2008) and Godhavn *et al.* (2005). NeuroSolutions 5.0 software was used for neural computations.

The modeled system included two oil/gas/water separation vessels, a suction scrubber unit (to remove any solids from the gas stream) and two compressors, namely, A and B. The two compressors are connected in parallel for gas export to onshore (see Figure 4). Separator 1 is smaller in size to pre-separate the hydrocarbon streams, whereas separator 2 is a bigger vessel with Low Pressure (LP) separation. Several variables were selected throughout the system, which included levels of liquids in the two separators, vessel pressures, outlet pressure and levels in the suction scrubber, inlet/outlet pressure and flow of the two compressors. Flow and outlet pressure of both compressors were taken here as representative for overall compressor performance as any suboptimal behavior of the compressors can be easily detected by flow and/or pressure fluctuations.

Figure 4 Schematic diagram of separation process



As aforementioned, liquid slugs and surging operational/flow conditions can cause high-level trips in separators that may result in the instability of the units in operation. This problem was modeled using the neural network approach to extract the useful information.

Data from a healthy system and faulty events is collected to perform the analysis. According to Principe *et al.* (2000), faulty data patterns in most cases can be easily identified as those with higher standard deviations. Table 4 represents 6 data patterns to capture traces of any abnormality. These included three fault-free (incident-free) operational months and three months' data where signs of suboptimal performance were seen. Data from separator 2, suction scrubber and compressor A is given in the table below.

Table 4 Faulty and healthy data patterns

	Separator 2 pressure		*Separator 2 oil level*		*Scrubber pressure*		*Scrubber level*		*Comp. A outlet Pressure*	
Event	*Mean*	*St. Dev.*	*Mean*	*St. Dev.*	*Mean*	*St. Dev.*	*Mean*	*St. Dev.*	*Mean*	*St. Dev.*
					Healthy Data Pattern					
1	17	4	50	1.7	10	0.3	26	0.4	9.8	0.27
2	18	3.6	50	1.8	9.7	0.18	23	8.1	9.8	0.19
3	15	3.8	49	2	9.8	0.44	25	0.62	10	0.4
					Faulty Data Pattern					
1	17	4	49	2.6	9.4	0.92	25.1	1.64	9.8	0.9
2	17	4.3	51	2.8	9.86	1.2	26	2.3	8.5	3.8
3	19	5.5	47	6	9.7	2.1	25.5	3.6	10	4.85

Table 4 indicated that the mean and standard deviations did not suffice for classifying different data patterns. Therefore, in normal practices, these data sets might not be regarded as a good indicator of a fault. The reason was that most variables in this process were quite stable during daily operating conditions. In Table 4, only faulty pattern no. 3 showed somewhat significant deviations from norms.

As this behavior continued, significant changes were observed in the suction scrubber unit. The source of these disturbances was a scheduled maintenance operation that created fluid levels and a pressure rise in the separator vessel. Consequently, the gas compressors suffered severe pressure fluctuations that later resulted in the tripping of the gas compressors.

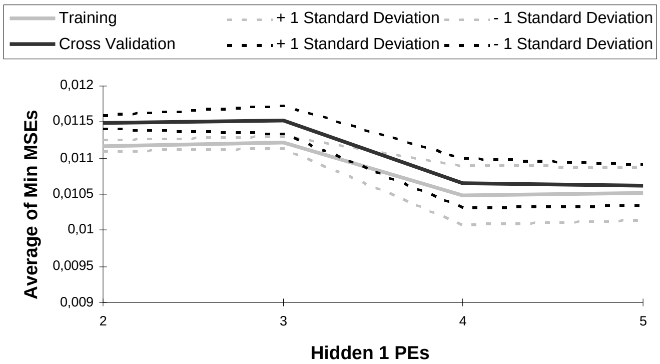
Data from this example was selected to show how neural networks can predict these seemingly undetected changes that might affect the integrity of the whole system. Neural networks are quite famous due to their well-established learning and adaptive capabilities. One of the capabilities of neural networks is the property of modeling an unknown function of a process. This learning property of the neural networks discovers the unknown function *f(.)* given a finite number of input-output pairs. This unifies applications of regression and classification in a more general problem, commonly known as *function approximation* (Principe *et al.*, 2000). Function approximation seeks to describe the behavior of highly complicated functions by ensembles of simpler functions. A Multilayer Perceptron (MLP) with one hidden layer network was trained to describe the behavior of hidden complicated functions.

To develop the base-line model of the process, the network was preliminarily trained for 5 months' operational data, including 14 inputs and 4 outputs. Data was divided into training, cross validation and testing sets. A model was developed and analyzed using NeuroSolutions 5.0 software. Mean Square Error (MSE) computed in each dataset was analyzed. It is the average of the square of the difference between the desired response and actual system outputs. This is a widely utilized performance criterion. Cross-validation was used as a criterion for stopping network learning (Principe *et al.*, 2000).

Cross validation computes the error in a test set at the same time that the network is being trained with the training set. It is known that the MSE will keep decreasing in the training set, but may start to increase in the test set. This happens when the network starts "memorizing" the training patterns. The error criterion component provides the values which can be used to measure the performance of the network for a particular data set. A sensitivity analysis was performed to measure how much a small change in one of the independent variables affects the functional value. Variables with the least effect on the outputs were removed during the modeling phase to improve the performance and simplicity of the network. As a result of sensitivity analysis, the number of input variables was reduced from 14 to 11. This process was repeated until we established the parameters of the base-line model.

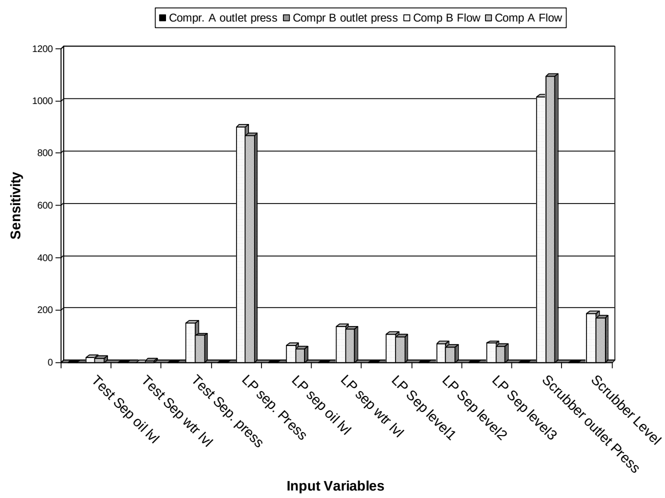
Figure 5 shows training and cross validation sets in the training dataset of the base-line model given with standard deviation boundaries. Computed MSEs were reasonably low with increasing numbers of processing elements in the hidden layer.

Figure 5 MSE in training the base-line model



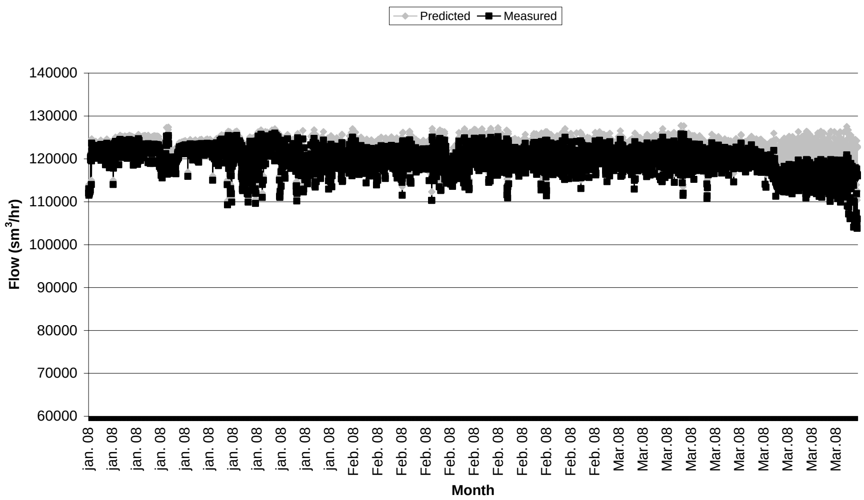
In this case, a total of 4 Processing Elements (PEs) were selected in the training model. The total number of PEs in the model is a characteristic of the software that is used to build the neural networks. Results from sensitivity analysis to estimate the influence of each input to the network outputs are shown in Figure 6. It showed that compressors' flow is significantly affected by separator 2 (LP) pressure and suction scrubber pressure whereas compressors' outlet pressures were not influenced by any input variables. Therefore we nominated compressor flow as the critical indicator of suboptimal performance. This can be clearly seen as a larger influence (bars in Figure 6) on the network outputs. This was also validated by the historical data and domain experts.

Figure 6 Sensitivity analysis using Neural Networks



The base-line model was then tested for unseen data (dataset not used during training phase) which showed satisfactory network performance. The neural network's adaptive capabilities can detect signs of degradations by deviations from the network-predicted and the real values. Again MSE was the judging criterion in analyzing the network's performance. This base-line model was tested for data from compressors from January-March 2008.

Figure 7 Symptoms of abnormality in compressor A



There were no significant deviations seen in compressor B data, whereas gradual reduced flow from compressor A was seen in the network predicted values (see figure 7). When checked with historical data, this behavior was recognized as indications of a hidden fault that led to shutdown in the corresponding month of May 2008. At this stage however, there were no indications of any abnormalities in the system as seen in the existing monitoring and control systems.

The neural network model clearly showed that, by carefully selecting the input parameters of the system, these networks can efficiently identify symptoms of abnormality in the system. If this had been a part of normal monitoring and surveillance system, these symptoms could have initiated a system reconfiguration in order to restore normal operation. The indicators from sensitivity analysis in Figure 6 provide an estimate of which variables could be controlled in order to avoid any unwanted consequences.

This is an excellent example of a trained neural network detecting abnormality in the real plant process data. This could give an excellent opportunity to the system experts and operators to identify abnormal behavior of the equipment early and take the necessary actions to restore to the original operating conditions. The restoring process may include inspection requests, changing operating conditions and/or recommendations for predictive maintenance plans etc.

4 Discussion

The case study raised several critical issues as a part of the main focus area. The first part of the study discussed issues on domain experts' level. It summarized technological gaps, possible areas of improvements and emphasized selecting a suitable strategy incorporating experts and streamlined information from production databases. The analytical part of this context used real plant data to model a particular scenario that took place in the past. It showed that carefully selected model inputs can predict the suboptimal performance of equipment to a reasonable level. The model successfully captured early signs of faults in one of the compressors. It further showed that compressor A was more vulnerable to process changes with respect to the changes in the process. Moreover, the network also highlighted contributing critical indicators that showed which variables may potentially be responsible for this abnormality. Experience with the neural network further showed that properly trained models can capture valuable information and can predict system performance that is apparently undetected by standard monitoring and control systems.

5 Conclusion

This paper reflected the use for an Artificial Neural Network (ANN) approach to model highly complex non-linear data from an offshore O&G production plant. The case study demonstrated how neural networks can learn and extract useful information from input data, ultimately transforming it into useful information about the system's condition. Past experience showed that, in most cases, early indications were often either misunderstood or undetected by existing monitoring systems. These indicators can play a vital role in reducing uncertainties associated with the events. The case study also concluded that appropriate use of qualitative and quantitative data to explore opportunities plays a vital role in defining a suitable strategy. Digital infrastructure for data acquisition has already been established in bigger oil and gas operators and the greater need is to use available resources efficiently for enhanced surveillance and monitoring of the assets.

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