

Management by Exception Surveillance Data for Well Management for Maximizing Oil Production

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Summary

Current economic realities have pushed oil and gas company to produce “more with less”. The ever-increasing amount of data available to surveillance engineers has caused engineers to spend more time gathering, analyzing them manually which is a daunting exercise and inefficient. The time-consuming process of analyzing surveillance data of a well with unexpected well shut-in time is able to cause a huge loss in a production operation. By leveraging on data-driven surveillance by adopting the principle of management by exception (MBE), the project tries to minimize the manual interaction between data and engineers. The project will be focusing on analyzing the surveillance data from 26 wells of 3 different fields located in North Sea and the data that will be used in the study is the production data in terms of oil production rate (bbl/day), and the time (year) for each well with cross-checking the water cut and gas oil ratio. The study will also focus on the surveillance data in the absence of reservoir characteristics. The objectives of the study are to study the trends of production data available and to design an anomaly detection model (with a certain algorithm) that is able to identify any deviations in production trend. Anomaly detection will be used to gain insight of when the well be offline if the problem keeps on persisting without immediate action from engineer. In order to meet the objectives, data preparation process will be done before developing the anomaly detection model (with a certain algorithm). The trends and analysis of the data will be done in both Microsoft Excel and Python while the anomaly detection model (with algorithm) will be developed by using Python.

Keywords:

Anomaly detection; well surveillance; oil production prediction

1. Introduction

Big data technologies yield perspective and appliance that are necessary for the ambitious expansion of the oil and gas industry. It is of the strong concern to the operation and production work as it can forecast the future performance based on the historical outcomes and can be utilized to relocate assets to some better productive zones [1]. Under current economic circumstances, it is the time for the oil and gas companies to start producing “more

with less”. The huge number of production data available to the surveillance engineers have caused lean concepts to be used in which the surveillance engineers can focus on the highest priority of task while removing the unnecessary measures in the ever-increasing amounts of data available. The lean concept that has been introduced is called Exception Based Surveillance (EBS) and it is done by analysing over a huge amount of data and monitoring the exception conditions to alert a situation when there is a problem occurred instead of analysing all the problems occurred without making an exception on the data being analyzed [2].

Inside the oil and gas industry, predictive analytics are constructed based on the previous investments in the enterprise asset management (EAM) systems, merges real-time data from sensors and other acquisition methods with historical data to forecast possible asset failures, and allows the move from reactive (scheduled, break-fix) to proactive (condition-based, preventive) maintenance. Hence, by applying analysing data correctly, proactive surveillance can be applied in which it can help forecast the problems within any well before they occur and assists engineers to spend more time on the solution to the consequence of the problems and reserve them from the surveillance data obtained.

The number of data that the surveillance engineers be required to analyse from day to day is big, which has caused a lesser amount of time available for engineers to analyse and produce the solution to the problem occurred. This is because most of the time were spent on detecting any problem that occurred within the wells of the operation. Hence, within the scope of this project, problems that are listed below will be addressed by accomplishing all tasks planned:

- 1) Over-processing of data as the exception conditions that are listed has not been specifically introduced;
- 2) The time-consuming process of analysing surveillance data of a well;

- 3) Improper analyse of production surveillance historical data;
- 4) Unexpected well shut-in time in a short period which has high possibility to cause a huge loss in a production operation;
- 5) Improper planning of asset management in the production sector of an oil and gas operation due to not being able to forecast properly on the problem that occurs in any oil and gas well.

The project will be focusing on developing an algorithm that can analyse the surveillance data of an oil well based on the historical data of the wells. The key goals in the analysis the algorithm development are;

- 1) To discover the predetermined behaviour and irregularity of the surveillance data;
- 2) To study the trends of production data available to find a possible correlation between the current data and the future data;
- 3) To design an algorithm that detects a deviation in surveillance data and detect anomalies before the well will be shut-in (if difficulty persevere).

The objectives of this paper are to present the data pre-processing activity whereby the analysis of parameters correlation is presented, and to present the anomaly prediction results. This paper is organized as follows; the next section contains literature review that shares the related works and technologies. It will be followed by data preparation section, and results and discussion section. Then the conclusion section will be presented to summarize the work as well as outline the future works.

2. Literature Review

Management by Exception is a term referred to the Exception Based Surveillance (EBS) tool. By applying this concept in managing oil production operation, it can help the surveillance engineers to concentrate on the greatest value of tasks and eliminating unnecessary analysis [3]. EBS implements the lean principles:- focusing on a few numbers of waste to avoid over processing when exception conditions were met [2]. According to Ref. [3], three intangible benefits particularly attributed to EBS are:

The gap between actual production and the well potential are reduced by supervising the wells within their window of operation. The risk of experiencing deferment is reduced as well as the cost of production operation as corrective intervention is being taken into measures. The more intelligent way of working able to bring positive energy to the surveillance team as well as boosting the productivity.

2.1 The process of analyzing surveillance data

One of the fundamental steps for reservoir development is the analysis of the production data as it is very important for the petroleum industry especially in the upstream sector of the industry [4]. A huge amount of surveillance data of oil and gas fields is collected every day, the most concrete ways to analyse this data is by using predictive analytics which it uses the data from the past to analyse the present and forecast the future [5]. By analysing the surveillance data, it can help in extending the lifespan of the oil and gas well and enhance the availability of production assets for other production zones [6].

In order to analyze the surveillance data using Big Data analytic method, one of the intelligent computation techniques in the computer science can be used by developing the self-adapting bionic optimization model [4]. This self- adapting bionic optimization model is developed by using data from monthly oil, gas, and water distributed volumes and information of working days (if available) in order to accurately predict future volumes [5]. This surveillance data can be analyzed using data clustering method [4]. This data clustering method utilized the unsupervised learning of patterns (observations, data items, or feature vectors) which are put into groups so that that the beginning understanding of the available data can be obtained [4]. One of the clustering methodologies is by performing a grey correlation analysis in which it describes the initial correlation between decisive parameters with production data [4]. This grey correlation uses limited known information in order to predict the unknown information, in which the word "Grey" itself means that information is incomplete [4]. By applying this intelligent computing technique, implicit patterns or trends can be revealed over different reservoirs, and also it helps to explain the clustering model by comparing the distributions of these patterns [4]. Fig. 1 illustrates the one of the of alarming graph based on "management by exception" concept.

2.2 Anomalies detection in Petroleum industry applications

Ref. [7] stated that anomaly detection is the obstacle of searching for patterns in data that do not confirm to an expected behaviour of data. Anomalies can also be presented as outliers when there are some data samples which deviate at a distance, from the rest of the dataset. As anomaly detection has attracted a lot of attention of the research community, its relevancy can be seen in the real-life applications such as intrusion detection, fraud detection, fault detection and system health

monitoring. As anomalies can either produce positive or negative results, the petroleum industry is also affected by these problems. However, the decision makers have to take appropriate measure in order to interpret such anomalies with the best expected results depending on the context and nature of the anomalies.

According to Ref. [8], by detecting anomalies in oil well surveillance data, it can help minimizing the manual interaction between data and engineers. The benefit of early anomalies detection in oil well surveillance is that it will allow for immediate and proactive measures, faster response time for well intervention activities, minimize well downtime, also safeguard the well production as well as cost saving. By detecting anomalies at early stage, it can provide a heads-up to engineers before it is too late for corrective action. In detecting anomalies in surveillance data, surveillance engineer identifies compelling events which deviate from a standard. In a practical manner,

anomaly detection in surveillance data is done by comparing actual measurements or values with a set of target value (performance) that are anticipated as a priori. By doing this, the surveillance engineer may attain a list of situations that fall outside accepted set-point boundaries.

Principally, one producing well should have a production trend that is certain. For instance, a producing well with a certain oil production, water production and gas production; the trend for the next 1-3 months will not deviate much from these figures unless there are a few problems that occur at downhole or at reservoir level. A sudden increment in the oil water-cut and gas-oil ratio in oil producing well will cause the oil production to drop. Too much anomalies or deviation from the expected production level will cause the well to be offline for investigation and intervention activities if necessary.

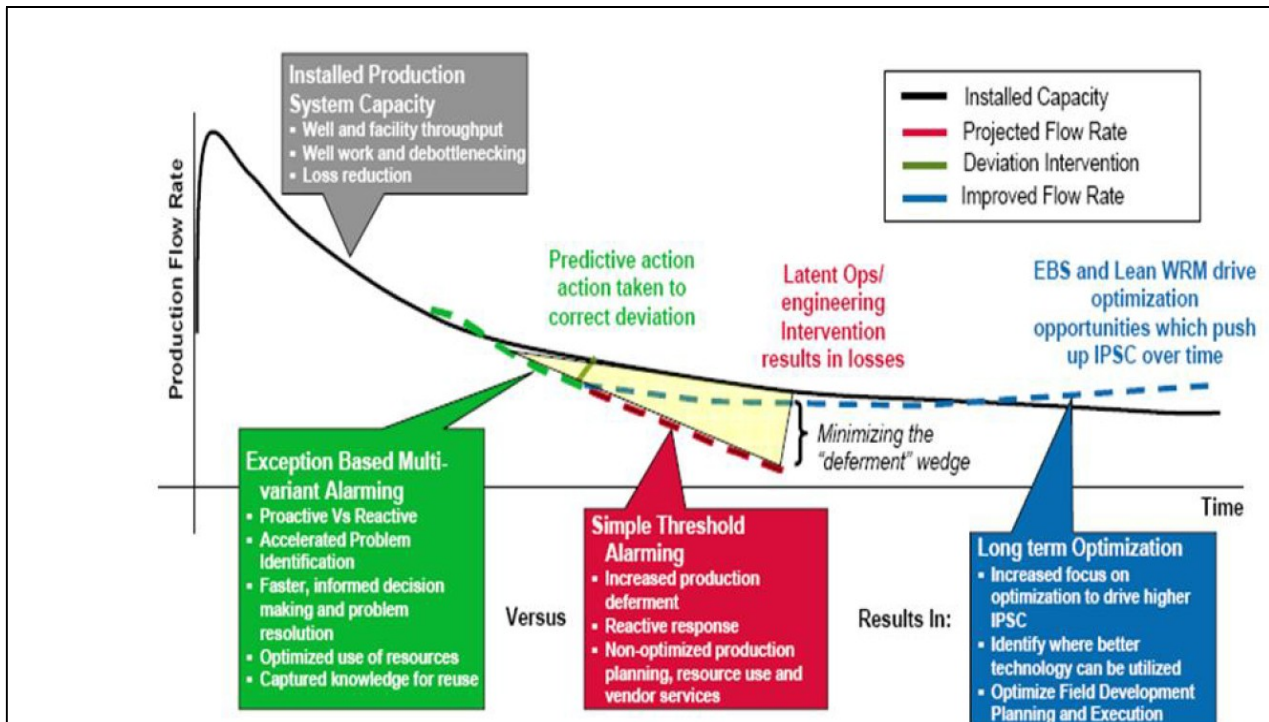


Fig. 1 Exception Based Alarming Graph [2]

2.3 Artificial Neural Network

Generally, neural network is a tool that is designed to mimic the way in the way of how one's brain performs a specific task. It is a huge processor that is distributed in a parallel manner which is made up of simple processing units that can store experiential knowledge and thus make

it available for utilization [9]. The artificial neural network features the brain in two aspects:

1. Knowledge is gained by the network from its learning environment through an iterative training process.
2. Interneuron connection strength is used to keep all the acquire knowledge. It is also known as synaptic weights.

Artificial Neural Network (ANN) can be described as system that channels the information based on biologically nervous systems similar like human brain processing information. The main idea of ANN model is that it resembles the human biological nervous systems where a huge number of interconnected processing neurons perform together to untangle a problem. As ANN resembles how human being learn by example, it follows the procedure of a learning process which is called learning algorithm. The learning algorithm has adjustable synaptic weights of the network which are able to meet required design objective.

2.4 Artificial Neural Network in predicting oil flow rates

Often, the estimation of oil production flowrate through a not feasible direct rate measurement become the challenge that is faced by oil and gas producing companies. In some situations, the oil flow rate is estimated using sort of empirical correlations in which in certain cases, it produces a huge error and yields results with very low accuracy. Thus, Artificial Neural Network (ANN) has turn into a key to solve old and new petroleum engineering problems by observe, recognize, and define the oil and gas problems in a way that will be addressable by the neural networks [10]. Even the first application of ANNs in petroleum engineering was done by Ref. [12]. Ref. [13] also mentioned that the ANN has been used in many aspects of petroleum engineering, like reservoir characterization, two-phase flow in pipes and permeability prediction for the last two decades.

Usually, the oil production flow rate is being controlled by wellhead chokes in order to bring the flow rate to desired levels for various functions. In real field conditions, there is a two-phase of fluid that flow through choke which is the oil and gas. Ref. [13] stated that there are number of correlations that can be used in order to predict the oil production flow rate from the given field production test data. correlations are developed either theoretically or empirically and either need experimental or field data in order to compute the oil production flow rate. However, correlations have two main challenges in which the first one, for the theoretical correlation, it has too many parameters which caused it difficult to be applied in the petroleum industry because process of gathering the information for these parameters are costly and also time consuming. Secondly, the main challenge that need to be faced when using this correlation is the empirical correlation are limited in range of data and may be able to yield acceptable results only. Thus, in order to overcome these problems, Ref. [13] proposed a new methodology to predict oil flow rate in two-phase flow of

oil and gas through wellhead chokes using Artificial Neural Network. In developing the learning rule for the algorithm, a multilayer perceptron neural network was used while employing the back-propagation algorithm as the feed-forward and supervised Artificial Neural Network [14].

Based on previous works, Ref. [15] stated that the oil flow rate is a function of several factors such as the choke upstream pressure, size of choke, producing gas to oil ratio, and specific gravities of oil and gas. However, Ref. [13] only set the choke upstream pressure, choke size, and producing gas to oil ratio as the input parameters for the Artificial Neural Network (ANN) model and predicted oil flow rate as the output parameter. For the ANN, there is one hidden layer inside the network as according to Ref. [16], one hidden layer is adequate if number of neurons in making the network is sufficient. This is because more number of hidden layer will cause the amount of time to train and test the algorithm to be longer. As number of neurons in the hidden layer determined by trial and error practice, the best network was able to be designed in order to create an algorithm that can predict oil flow rate [13]. Fig. 2 summarizes the neural network that was used in the study of predicting oil flow rate using ANN. The network has three layers with 3 neurons in the input layer, 4 neurons in the hidden layer and 1 neuron at the output layer.

The neural network designed require transfer functions for its hidden layer and output layer such as tan-sigmoid and linear transfer function. In making the ANN algorithm for predicting oil flow rate, data given need to be separated into testing data and also training data as shown in Table 1.

An improved step for the development of the ANN is required in the methodology as shown in Fig. 3.

ANN model is able to give greater predictions and more accurate result for oil flow rate values [13]. This is because the ANN model achieves the lowest average absolute relative error, lowest minimum absolute relative error, lowest maximum, absolute relative error, and lowest average relative error as shown in Table 2.

Meanwhile, ANN model also was able to achieve highest correlation coefficient as determined using R squared method. This was proven by the cross plots of the predicted oil flow rate versus actual oil flow rate for the ANN model correlation as shown in Fig. 4.

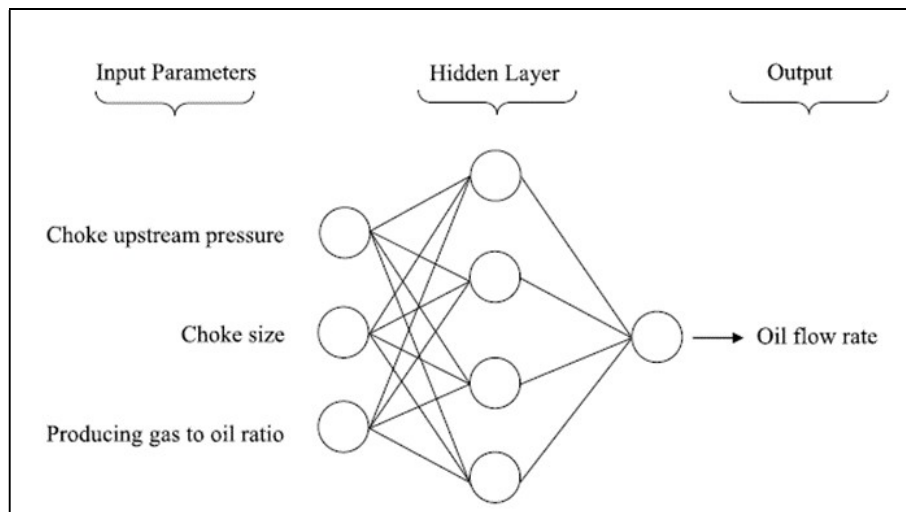


Fig. 2 Neural network architecture used in this study [13]

Table 1 Range of data used for training and testing stages [13]

<i>Range of data used for training and testing stages</i>		
<i>Type of data</i>	<i>Range of data used for training stage</i>	<i>Range of data used for testing stage</i>
Oil flow rate, STB/day	198-9643	282-8464
Choke upstream pressure, psia	115-4308	198-3974
Choke size, 64th of an inch	16-128	16-128
Producing gas to oil ration, SCF/STB	158-6100	192-5511

Table 2 Statistical parameters for the oil flow rate correlations [13]

	<i>ANN</i>	<i>Gillbert</i>	<i>Ros</i>	<i>Baxendell</i>	<i>Achong</i>	<i>Mirzaei-Paiaman</i>
Average relative error, %	-0.33	-1.85	-15.39	-22.44	-32.89	-1.13
Average absolute relative error, %	2.11	17.19	21.06	26.62	36.48	9.31
Minimum absolute relative error, %	0.54	1.07	0.88	1.79	2.87	0.76
Maximum absolute relative error, %	6.38	39.99	50.46	68.15	103.33	46.24

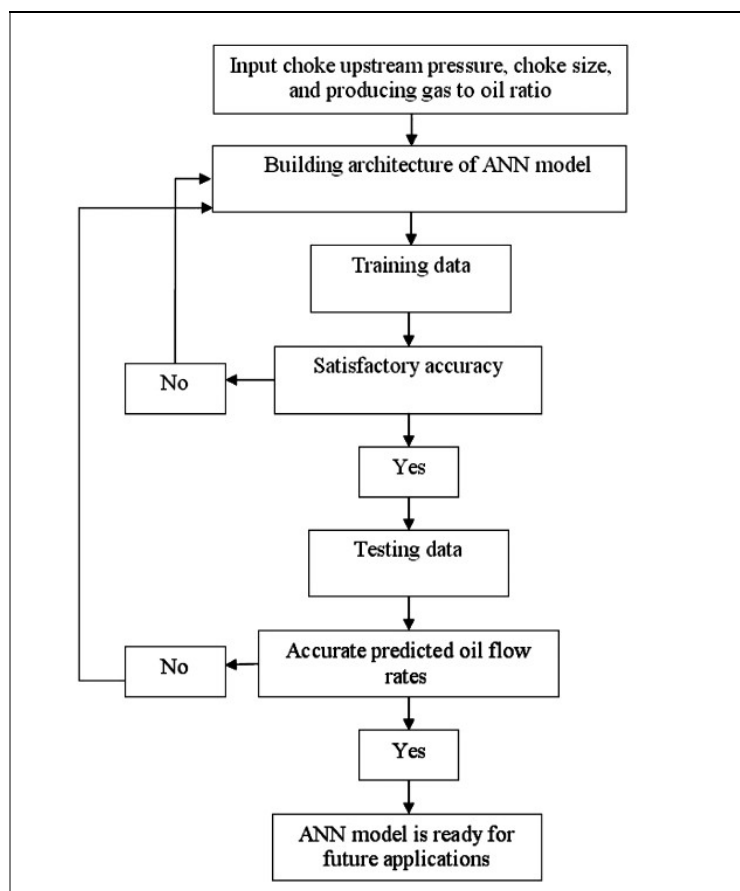


Fig. 3 Different steps for ANN methodology, predicting oil flow rate [13]

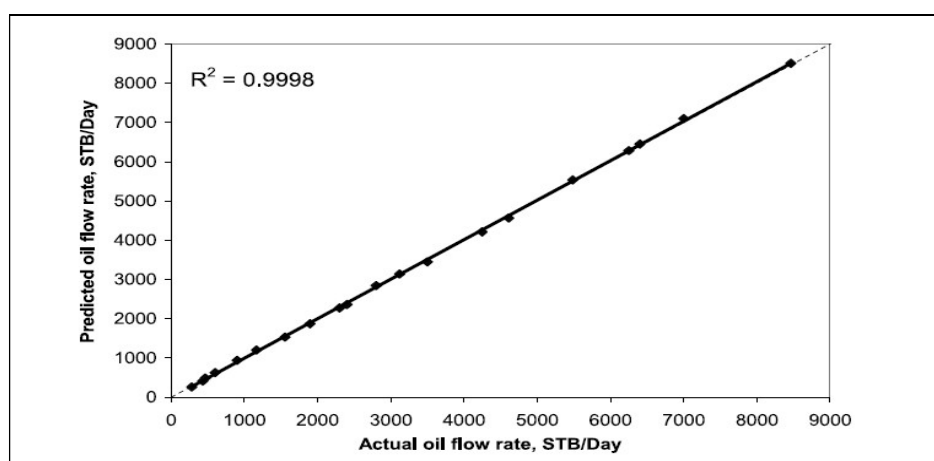


Fig. 4 Cross plot of oil flow rate for ANN model [13]

3. Data Pre-Processing

The project is focusing on developing an algorithm to analyze production or surveillance data from 3 fields in North Adriatic Sea which are Abroath field, Alwyn North field, and Alba field for a period of 12 years (1987-1999). Data that will be studying is the oil production rate(bbl/day) with time (year) as well as cross-checking with the gas-oil ratio(Mscf/bbl) and water cut (fraction).

In order to investigate the effect of these 3 parameters, a correlation heat map is made by using the Python software, it can be seen that both water cut and gas-oil ratio does have a sufficient effect on the oil

production rate from the correlation heat map generated as shown in Fig. 5.

Correlation heat map allows an observation of the relationship between one numeric feature towards another numeric feature. Correlation value is between -1 and 1 and it represents how closely these 2 features move in unison. Positive correlation (0 to 1) shows that if one feature increases, another feature increases meanwhile negative correlation (0 to -1) shows that if one feature increases, another feature will decrease. A strong relationship between features can be indicated from a correlation close to 1 or -1 meanwhile a correlation value that is close to 0 portrays a weak relationship. Thus, it can be seen that both water cut, and gas oil ratio has negative correlation towards oil production data from Fig. 5.

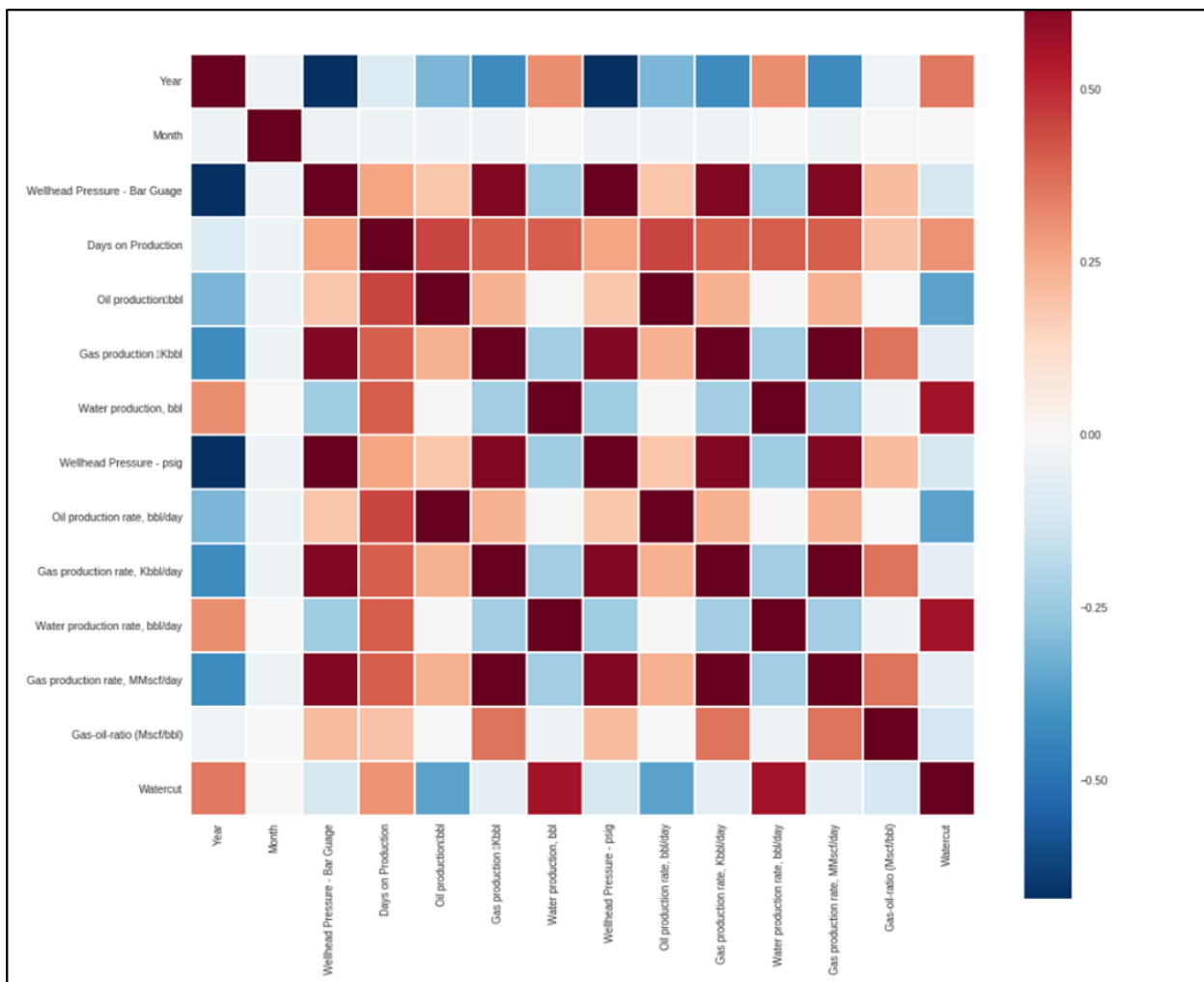


Fig. 5 Anomaly detection (statistical based) on well 22/17-T1 (Arbroath section)

4. Results and Findings

Based on the objective of this project, there are 4 manipulating variables that need to be tested which are the oil production rate (bbl/day), time (month), gas-oil-ratio (Mscf/bbl), and water cut (fraction). The first variable which is the oil production rate (bbl/day) will varies differently according to the values of the remaining two variables which are gas-oil-ratio (Mscf/bbl), and water cut (fraction). According to theory, when the water cut value is high, the oil production rate will reduce. If the situation persists, there will be a high possibility for the well to be shut-in if the water production has exceeded the limit set by one operator or client at the production platform. This also applies to the increment of the gas oil ratio in it will reduce the oil production rate and have high tendency to cause the well to be in a shut-in condition if there is no action to be taken towards the well that has this kind of problem.

By analyzing the four variables stated, the first objective of this project is met which is to study the trends of production data available in order to find a possible correlation between the historical data. The trends of the production data are analyzed by using Python software through the plots of the oil production rate (bbl/day) against the water cut (fraction) and also gas-oil ratio

(Mscf/bbl). Thus, the data that produce good trend are given priority in order to be chosen as the data set that will be used in developing the algorithm of the anomaly detection model to detect anomalies in negative oil production trend.

The result from simple anomaly detection by setting up the rules of anomaly should occur before the oil production rate (bbl/day) drop when the watercut (fraction) or gas-oil ratio (mscf/day) increase is shown in Fig. 6. Red dot represents the GOR anomalies while blue dot represents the watercut anomalies. From the original plot, there are too much anomalies and this could be confusing for the oil company later on.

Thus, by using simple moving average anomaly detection, more accurate result of when anomaly occur is obtained. This is because utilize the average of past data in order to estimate the present value.

Thus, it can be seen clearly from Fig. 7, anomaly detection occurs on month 38 and also month 64 for the well 22/17-T1. Thus, the oil operating company should have taken an action before the anomaly happens as after the anomaly occur in Fig. 7, it can be seen that the graph continues to drop down till a very low value of oil production.



Fig. 6 Anomaly detection (statistical based) on well 22/17-T1 (Arbroath section)

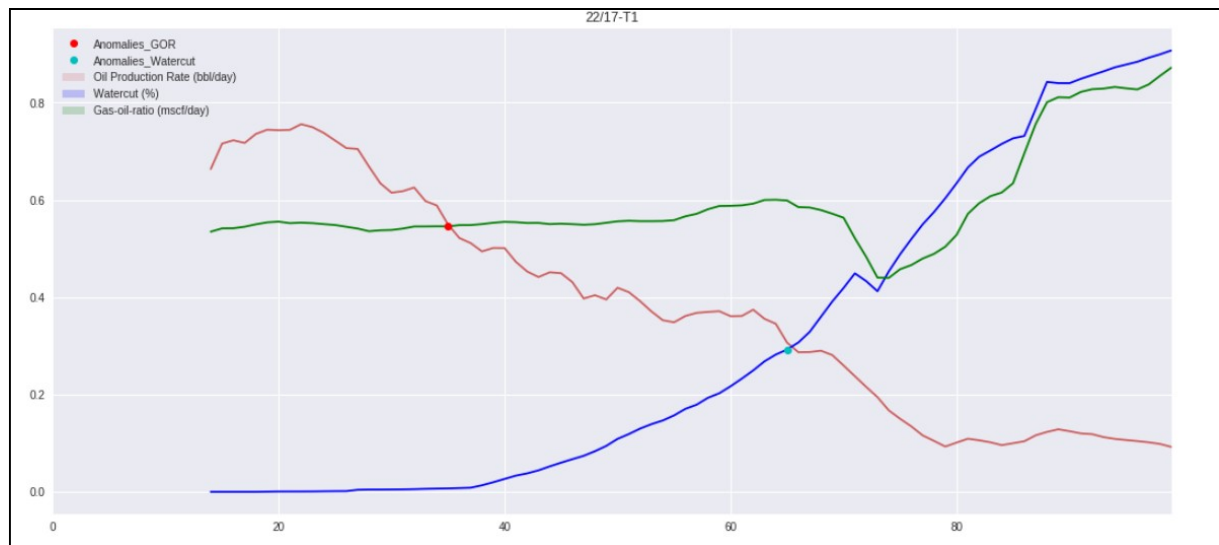


Fig. 7 Anomaly detection (statistical based) by using simple moving average method on well 22/17-T1

5. Conclusion

As surveillance engineers have to deal with a huge number of data daily, more time was spent on analyzing the data and detecting the problem while having insufficient time to produce the solution the problems encountered. With the help of Exception Based Surveillance (EBS) together with anomaly detection model using Python (Artificial Neural Network), surveillance engineers can analyze the ever-increasing amount of production data in a shorter time while being able to detect anomaly when the well going to start to initiate problem. Because of the shut-in well can reduce high amount of cost in order to stabilize the well back for production, proactive measures can be taken using the anomaly detection models produced. A better version of anomaly detection models can be created with more data available to the be the input of the algorithm.

In the future, this work will further develop the algorithm to forecast oil production trend together with the gas-oil ratio and also water cut so that the similar concept of anomaly detection in this project can be applied. By applying the concept of this project, the researcher will be able to forecast when the anomaly will occur for oil production data for one well in which this in the future will help the oil companies to save more money for their production and well intervention operation as they are able to forecast when the anomaly will occur in their well. An improved quality and up to date data also are recommended to ensure the result obtain are more accurate.

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