

Performance Data Analytics for Contact Cooled Rotary Screw Air Compressors



Xavier Chelladurai, Suraj S. Jain, Aryan Soni Burman, Sonal Kumar, Sindhu Srinivas

Abstract: The operations management of air compressors gets transformed from the traditional reactive approach to the proactive data analytics based one. While large volume of data is analyzed, it is important to identify the parameters that cause performance deterioration. This helps in the preventive maintenance and increases the system availability to a great extent. In this research, we propose an approach to identify the causal parameters and test them in a practical customer environment. We have analyzed the data pertaining to Contact Cooled Rotary Screw Air Compressors from a customer's site. The system is controlled by XE-90M/145M controller. The controller continuously monitors 85 parameters and values collected every minute and uploaded to the cloud every 15 minutes. We analyzed the data for all the parameters, identified the upper control limit (UCL), lower control limit (LCL) and mean values. Using the historical data of drip of compressors, we have analyzed the data and classified the parameters into two categories, parameters which causes the performance deterioration and the ones that goes abnormal as a consequence of performance deterioration. Also, the study has discovered that the causal parameters show performance deterioration symptoms during a window of one to three hours before the actual drip happens. This has helped the customer to proactively do the corrective actions in the window and avoid drip of the compressor.

Keywords: Predictive maintenance, Data Science, deep learning, compressors, machine learning, data analysis

I. INTRODUCTION

In recent years there is an increasing interest among research communities to apply data science techniques to predict and improve the performance of almost every

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operational and business systems. Air compressors are no exception to this trend. This is partly because of the availability of proven data analytic technology but mainly due to the fierce competition in the market in getting the technology support to make the customer experience better and competitive. In the process plants assuring safety and optimal operative conditions is one of the primary goals of process plants. The paradigm shift from reactive or corrective maintenance to pro-active or predictive maintenance is the key-driven in applying data analytics approach for the best possible result. In this research, we have applied data analytics approach to narrow down on the parameters causing the performance deterioration in contact-cooled rotary screw air-compressor.

II. BACKGROUND

Data Analytics best practices derive data scientists to be working with a fair level of domain knowledge. This is because of the creative approach requires an understanding of numbers, their ranges and their meaning. Also, the data analyst must be able to interpret the variation of one parameter over a period of time and also the relationship between different parameters.

In this section we describe the key facts about the operations of a typical air compressor system. The air compressor system works with a package having the following key components:

1. Air Receiver Dry Tank
2. Air Receiver Wet Tank
3. Air Dryer

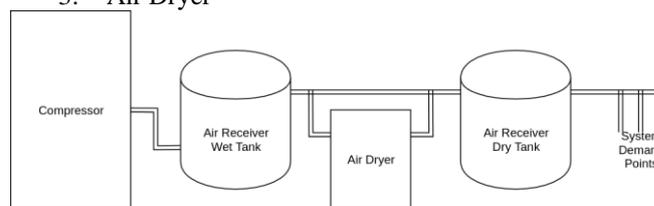


Figure 1 Compressor and air system

In the interconnection among these components there are valves with temperature and pressure sensors at the input and output point. The following section describes the working of the compressor at a high level. The following are the key components of the coolant system:

1. Sump
2. Cooler
3. Filter
4. Thermostatic valve
5. Separator tank

The air pressure causes coolant from the separator tank to the thermostatic element.



In order to maintain the optimum compressor discharge temperature, the position of the element makes one of the following three directions:

1. Coolant circulates through the cooler.
2. Bypass the cooler.
3. Mixes the two paths together.

The optimum temperature is controlled for the operating environment at the required level.

The coolant is injected at a sufficiently high temperature and the discharge air coolant mixture is maintained at the desired temperature.

The compressor parameters are managed by sophisticated controllers. In our research we have got data from XE-90M/145M controllers

III. DATA COLLECTION AND PREPARATION

The data used in this research were collected from a customer's location in the USA and the details cannot be disclosed due to non-disclosure agreement. In the customer's location a contact cooled rotary screw Air compressor of variable speed is installed. The system is controlled by XE-90M/145M controller. The controller continuously monitors 85 parameters. These values are collected every minute and uploaded to the cloud every 15 minutes.

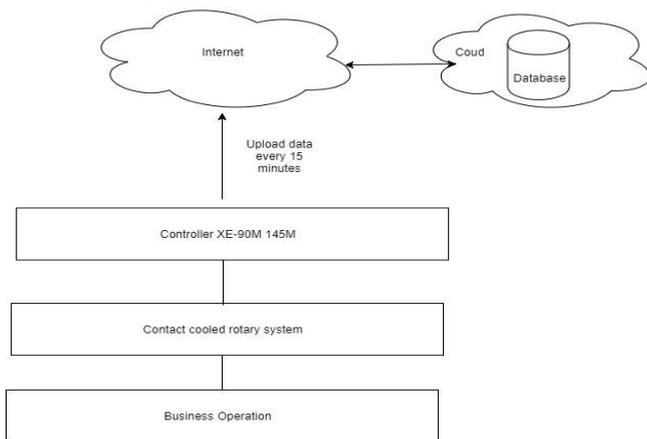


Figure 2 Controller uploads data to the cloud

The compressor parameters are managed by sophisticated controllers. In our re-search we have got data from XE-90M/145M controllers. Also, there were some missing values and we had a detailed discussion with the customer and corrected a few elements in 13820 rows.

There are certain fields which indicate whether a particular setting is enrolled. For example, the following some such fields:

1. After cooler discharge pressure
2. Auto restart delay time
3. Inter stage pressure
4. Lead lag cycle time
5. Modbus pressure unit
6. Modbus temperature unit
7. Oil cooler outlet temperature
8. Remote pressure
9. Scheduled start time of day
10. Scheduled stop time of day
11. Service level
12. Starter type

After discussing with the customer team, it was decided not to focus our re-search in these fields.

IV. DATA NORMALIZATION

In data science, when models are constructed with several fields, the relative comparison of values of multiple variables contribute to the accuracy of the model. For example, if one parameter has the values in the range of 0 to 1. An another with range 1,50,25,300 to 10,50,75,000 then the model may not be accurate. This is because the variation between two instances of parameter 11 and that of parameter 2 cannot be compared. In this research almost all the parameters are either temperature or pressure. Their values are comparable and hence it was decided not to normalize the data.

V. RANGE FOCUS

In this phase we selected rows and columns for detailed study from the large volume of data more than 4,70,000 rows and 85 columns. After detailed analysis it was decided to focus on 28 key columns listed in figure 3.

```
In [10]: df.columns
Out[10]: Index(['uctimestamp', 'yearmonth', 'cnfirmarev.1', 'controllertimestamp',
'activestartinhibitcode', 'activetripcode', 'activewarningcode',
'aftercoolendischargepressure', 'sirendischargepressure',
'coolantfilterinletpressure', 'coolantfilteroutletpressure',
'coolantfilterpressure', 'injectedcoolanttemperature',
'inletvacuum', 'loadetime', 'modeoperation', 'offlinepressure',
'onlinepressure', 'packagedischargepressure', 'runningline',
'separatorpressure', 'statusautorestart', 'statusloadunload',
'statusstartnotstop', 'statusstrip', 'statuswarning', 'statusword',
'sumpressure'],
dtype='object')
```

Figure 3 Columns selected for research

Customer gave a list of data and time at which the compressor tripped. The trip of the compressor causes business shutdown indicating a critical problem in the compressor system. So, from a business sense, a trip is critical. So, the objective is to analyze the root cause of the trip. For each trip we selected the rows with date stamp up to 2 days prior to the trip. The data is available for every minute. So, there are 1440 rows of data per day. This selection approach gives 3 days for detailed focus.

VI. DATA ANALYTICS

In this research, the focus is on 28 parameters and on a few time slots at which the trip happened. Among the 28 parameters are objectives to classify them into two categories: casual parameters, consequence parameters.

A parameter is caused if it contributes to the trip of the compressor. In other words, the changes in the value of this parameter has caused performance deterioration and finally resulted in drip.

The consequence parameters do not contribute for the performance deterioration. However, as a consequence of trip, the values of these parameters changed significantly.

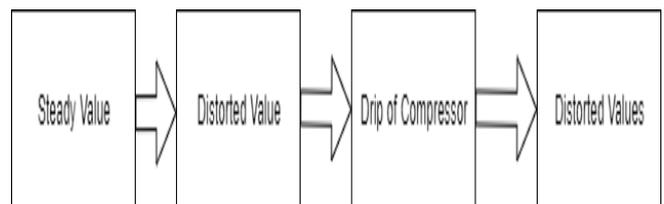


Fig 4. Casual parameter behavior

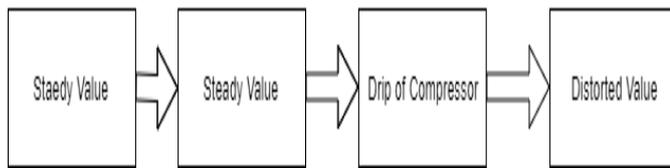


Fig 5. Consequence parameter behavior

VII. UPPER AND LOWER CONTROL LIMITS

Determination of upper control limit (UCL) lower control limit (LCL) and Mean value is an important activity in any data analysis project. In our research, on a normal day when there is no performance deterioration, the UCL and LCL are defined as follows:

$$UCL = \text{Maximum } \{x/x \text{ is a value on the day}\}$$

$$LCL = \text{Minimum } \{x/x \text{ is a value on the day}\}$$

$$\text{Mean} = \text{Mean } \{x/x \text{ is a value on the day}\}$$

VIII. PERFORMANCE DETERIORATION

A parameter is said to enter into performance deterioration if its value goes outside the range from LCL to UCL.

We have studied 32 parameters to see when they enter into performance deterioration. If a parameter enters to performance deterioration before trip and does not recover before the trip, such parameters contribute to the trip and called causal parameter or contributor for the trip.

If a parameter value deteriorates only after the trip, it is called a parameter deterioration as a consequence of the trip and hence called consequence parameter.

IX. ALGORITHM TO CLASSIFY CASUAL AND CONSEQUENCE PARAMETERS

Input: Data of 28 parameters for the time stamp every minute for 3 days.

Algorithm:

1. Find UCL, LCL and Mean for each parameter.
 - a. For each Parameter, calculate the UCL as the maximum value on the normal day when no trip happened.
 - b. For each parameter, calculate the LCL as the minimum value on the normal day when no trip happened.
 - c. For each parameter calculate mean of day value when no trip happened.
2. For each parameter p do the following:

If

perf deterioration in p before the drip and does not recover before the drip

then,

assign the parameter p as causal parameter

else,

assign the parameter p as consequence parameter.

End if.
3. Output causal and consequence parameters separately.

The above algorithm was implemented using Python and the results as follows:

A. Casual Parameters

The casual parameters are - After Cooler Discharge

Temperature, Air End Discharge Temperature, Injected Coolant Temperature.

B. Consequence Parameters

The consequence parameters are - Coolant Filter Inlet Pressure, Coolant Filter outlet Pressure, Coolant Filter Pressure drop, Inlet Vacuum, Package Discharge Pressure, Separator Pressure Drop, Sump Pressure.

X.EXAMPLES

A. After cooler discharge temperature for 02-01-2019

Let us consider the parameter, After cooler discharge temperature on 2-1-2019. There was a trip of the compressor on this day at 18:46. We analyse the parameter values for three days before the trip and a closer look on the day of the trip. UCL is 870, LCL is 840, and the mean is 855.

The three days value diagram is shown in figure 6. The detailed look of 2-1-2019 is shown in figure 8. We find that the values are within the UCL and LCL until 17:00 approximately. This shows that there is some problem with the system and the performance deterioration start from 17:00 which causes a trip at 18:46.

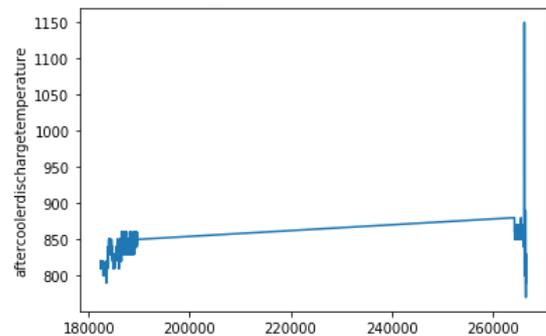


Fig 6. Three-day window of after cooler discharge

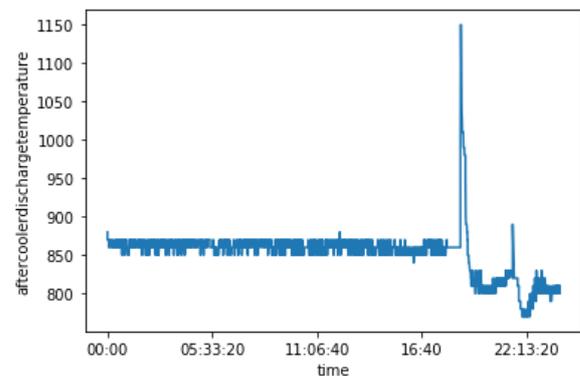


Fig 7. One day window of after cooler discharge

B. After cooler discharge temperature for 12-10-2018

A Let us consider the parameter, After cooler discharge temperature on 12-10-2018. There was a trip of the compressor on this day at 01:14. We analyse the parameter values for three days before the trip and a closer look on the day of the trip. UCL is 870, LCL is 800, and the mean is 835.

The three days value diagram is shown in figure 8. The detailed look of 12-10-2018 is shown in figure 9. We find that the values are within the UCL and LCL until 00:09 approximately.

This shows that there is some problem with the system and the performance deterioration start from 00:09 which causes a trip at 01:14.

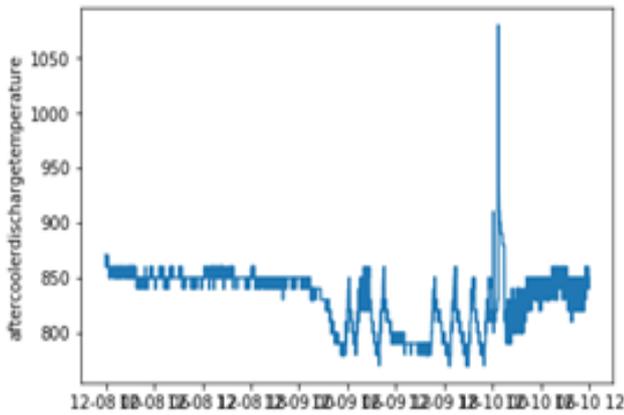


Fig 8. Three-day window of after cooler discharge

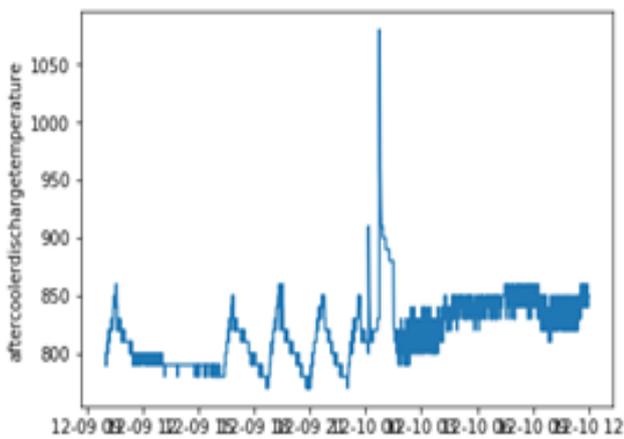


Fig 9. One day window of after cooler discharge

C. After cooler discharge temperature for 14-10-2018

Let us consider the parameter, After cooler discharge temperature on 14-10-2018. There was a trip of the compressor on this day at 22:51. We analyse the parameter values for three days before the trip and a closer look on the day of the trip. UCL is 850, LCL is 810, and the mean is 820.

The three days value diagram is shown in Figure 10. The detailed look of 14-10-2018 is shown in Figure 11. We find that the values are within the UCL and LCL until 18:46 approximately. This shows that there is some problem with the system and the performance deterioration start from 18:46 which causes a trip at 22:51.

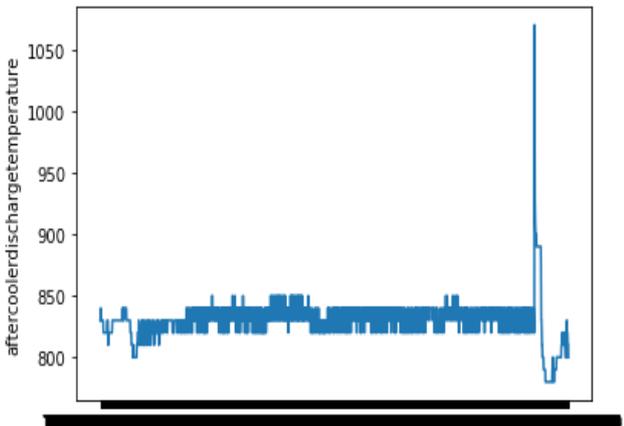


Fig 10. Three-day window of after cooler discharge

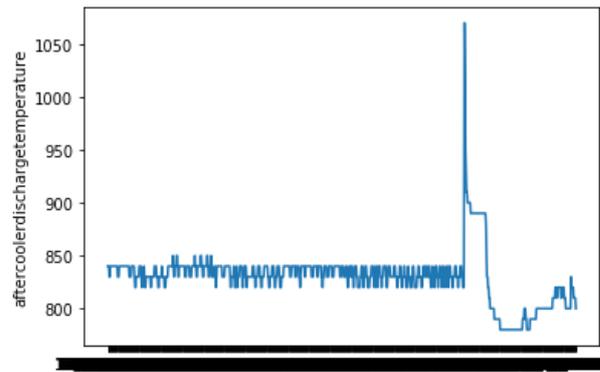


Fig 11. One day window of after cooler discharge

D. After cooler discharge temperature for 04-04-2019

Let us consider the parameter, After cooler discharge temperature on 04-04-2019. There was a trip of the compressor on this day at 16:48. We analyse the parameter values for three days before the trip and a closer look on the day of the trip. UCL is 950, LCL is 810, and the mean is 831.90.

The three days value diagram is shown in Figure 12. The detailed look of 14-10-2018 is shown in Figure 13. We find that the values are within the UCL and LCL until 16:39 approximately. This shows that there is some problem with the system and the performance deterioration start from 16:39 which causes a trip at 16:48.

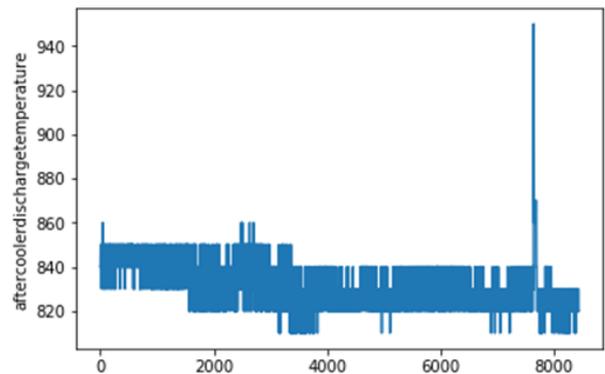


Fig 12. Three-day window of after cooler discharge

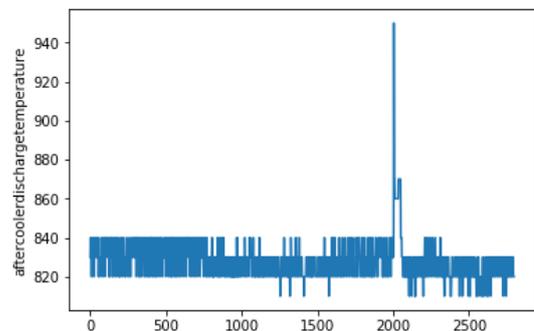


Fig 13. One day window of after cooler discharge

XI. RESULT OF THE RESEARCH

In this paper we have introduced a process to identify the causal parameters and consequence parameters. When tested the hypothesis with the data we have been successful in identifying the causing and consequence parameters. In this study the analysis of the data reveals the following results:

1. The following are the Causing Parameters
 - o After Cooler Discharge Temperature
 - o Air End Discharge Temperature
 - o Injected Coolant Temperature
2. The following are the Consequence Parameters
 - o Coolant Filter Inlet Pressure
 - o Coolant Filter outlet Pressure
 - o Coolant Filter Pressure drop
 - o Inlet Vacuum
 - o Package Discharge Pressure
 - o Separator Pressure Drop
 - o Sump Pressure

The performance deterioration window is shown in Table 1 for the four cases we analyzed. This shows that we must work on the alert got in the performance deterioration window and avoid drip of the compressor.

Table 1. Analysed performance deterioration window for compressors in the data.

Date	Performance Deterioration Time Stamp	Drip Time	Performance Deterioration Window
02-01-2019	17:00	18:46	1 Hour, 46 Minutes
12-10-2018	00:09	01:14	1 Hour, 5 Minutes
14-10-2018	18:46	22:51	4 Hours, 5 Minutes
04-04-2019	16:39	16:48	0 Hours, 9 Minutes.

XII. CONCLUSION

In operations management and control scenarios, digital controlling involves large volume of data pertaining to several parameters measured in frequent intervals. While analyzing the data and arriving at actionable insights, the first step involves identification of the key parameters which cause performance deterioration. In this research we have introduced a method and proved that it can be used for preventive maintenance.

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