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# Agile Development of Machine Learning (ML) for Conventional Artificial Lift Systems in the Middle-East

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## Abstract

The majority of Oman's southern fields are produced by beam-pumps which consist approximately 2,000 wells, globally beam pumps remain an extremely popular choice for secondary lift. Identification and diagnosis of beam pumps using dynocards is an expensive human visual interpretation process. It does not only require significant labor time but also requires deep expertise in the production technology domain. The development team had three goals: 1) use open-source analytics, 2) develop a Machine Learning application (ML) to solve business challenges and finally 3) foster solutions with significant value investment ratio (VIR). In this case, a proof-of-concept application was developed to automatically screen beam pump dynocards and identify abnormalities (e.g., electrical related failures) which cause improper operation of the well, leading to deferment, undetected by conventional monitoring systems, and/or mechanical damage.

To address the above challenges, an analytics minimum viable product (MVP) was developed for pattern recognition which significantly assisted in automating (analysis of a 100 hundred wells with real-time data in less than 1 second) the visual interpretation process, increasing efficiency, and reducing maintenance activities due to missed early diagnosis. It detects current and future abnormal conditions that cause improper operation of the artificial system to deferment and potentially to mechanical damage. This new app identifies and highlights these wells so that operations & maintenance staff can focus their attention where it is really needed, improving their workflows and decision making.

This paper outlines how applying Machine Learning (ML) along with the Scaled Agility methodology enabled the operator to develop an MVP and diagnose abnormalities on daily basis not raised by any other system. Of the 100 wells in the selected field around ~10% were identified with clear failures. This translated to approximate ~5 % improvement in lead indicator (prior to issues) detection projecting ~2.5 million USD in efficiencies and deferment reduction.

The cost of development in CAPEX was 0 USD as the team developed this purely on Open-Source platforms that were license free and on their own without the need of third-party application or resources.

## Introduction

The pathfinder initiative commenced in May 2019 with the aim of demonstrating that open-source analytics could be used to develop applications that solve business problems and deliver significant value. These applications could be developed rapidly, cost effectively, and could be commercialized or shared with open-source consortium partners. The approach combines engineering with data science to produce practical solutions that are easy to use and sustainable in the workplace.

The concept is to use open-source analytics and Machine Learning (ML) to solve business challenges and deliver solutions with significant VIR. In this case an application (which we dubbed AFKAR which roughly translates to "Insights" in Arabic) was developed to analyze the measurement data from the beam pump and detect abnormal conditions that cause improper operation of the pump and lead to deferment and potentially to mechanical damage.

The essence of AFKAR is that it analyses the dynocards that are created for each beam pump well and classifies them as Normal or Abnormal. In analytics terminology it is a binary classifier. AFKAR was used by the nominated Working Group for a period of 3 months and as part of the overall assessment a Blind Test was performed to generate a standard set of metrics that are typically used to measure how good a binary classifier is.

The use of Machine Learning (ML) and artificial intelligence for oil and gas applications started in the late 1980s, the new technologies related to The Internet of Things (IoT) in the earliest iterations were deployed in the oil & gas industry as early as the turn of the century. Wearable devices, vehicles, equipment, buildings, and just about any other thing can be embedded with electronics, software, sensors, and network connectivity. Increasingly, forward-thinking oil & gas organizations are focusing their IoT initiatives less on underlying sensors, devices, and "smart" things and more on developing bold approaches for managing data, leveraging "brownfield" IoT infrastructure, and developing new business models.

This "fourth industrial revolution", characterized by the convergence of technologies that blur the boundaries between the physical, digital, and biological realms, such as artificial intelligence, robotics and autonomous vehicles. Artificial Intelligence (AI) technologies are gaining considerable attention because of their rapid response speeds and robust capacity for generalization.[1]

Machine Learning (ML) is a computer system (and solutions) that can learn to perform automated tasks and think for itself through an algorithm that absorbs new data and experiences. ML starts working when a basic algorithm analyzes a large data set and then makes predictions based upon what it finds in the data. The algorithm will apply that knowledge to learn new ways of analyzing and acting upon future data sets. It's the perfect technology for automating tasks that require parsing large collections of data and making predictions with both speed and accuracy. Machine Learning (ML) is especially useful with data sets that are too large to analyze manually. More accurate results mean more efficient processes, which have benefits for safety, people, the environment, production, and profits.

In summary, when correctly applied to address a business problem, data analytics can improve asset productivity and reduce maintenance cost.

## Background

The most common type of artificial lift pump system applied is beam pumping, which engages equipment on and below the surface to increase pressure and push oil to the surface. It is roughly responsible for about two-thirds of the artificial lift producing oil wells. Consisting of a sucker rod string and a sucker rod pump, beam pumps are the familiar jack pumps seen on onshore oil wells.

Above the surface, the beam pumping system rocks back and forth. This is connected to a string of rods called the sucker rods, which plunge down into the wellbore. The sucker rods are connected to the sucker rod pump, which is installed as a part of the tubing string near the bottom of the well. As the beam pumping system rocks back and forth, this operates the rod string, sucker rod and sucker rod pump, which works similarly to pistons inside a cylinder. The sucker rod pump lifts the oil from the reservoir through the well to the surface. Usually pumping about 20 times a minute, the pumping units are powered electronically or via gas engine, called a prime mover. In order for the beam system to work properly, a speed reducer is employed to ensure the pump unit moves steadily, despite the 600 revolutions per minute the engine achieves. Figure 1 show typical beam pump equipment.

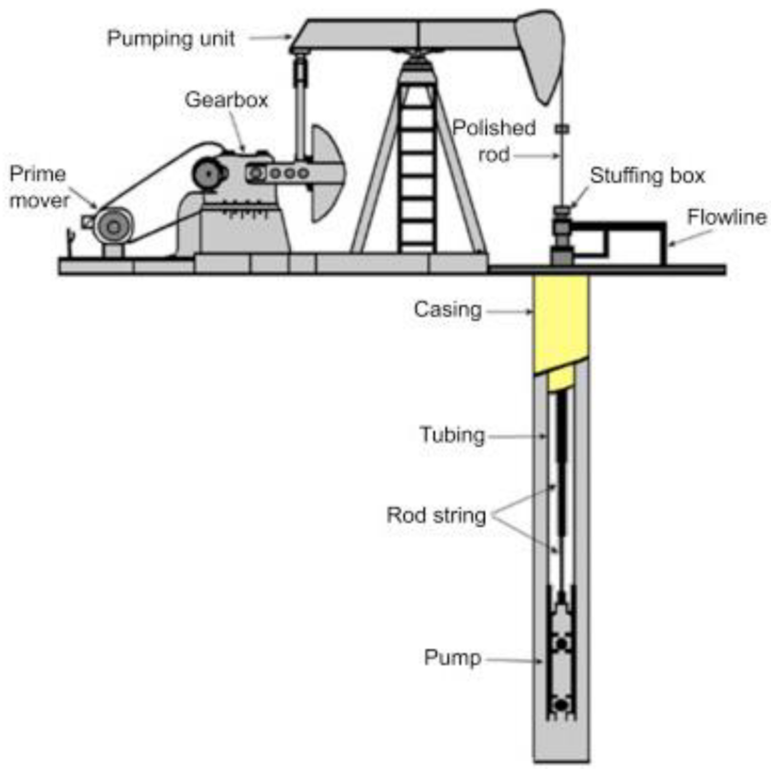



**Figure 1—Typical beam pump equipment.**

Well failures, including surface, reservoir and down-hole failures, in rod pump/beam pump artificial lift system commonly occur. Generally, the rod pump failures are mainly caused by improper design, improper manufacturing, normal wear and tear during operations, and excessive wear and tear due to sand intrusions, gas pounding, and asphalting. These failures initially reduce the efficiency of the pumping operation, but in the end will bring the systems to fail and require reactive well work. These workovers typically shut down the systems, leading to substantial downtime, production loss and operation expense, in addition to the regular maintenance cost. Quick and correct identification of well failure and scheduling appropriate maintenance will reduce wrongly planned repairs and minimize downtime, and subsequently improve the efficiency[2].

The main diagnostics tool for a rod pump system is the dynocard, which is graphical representation of the relationship between rod load and stroke position. There are two types of dynocards: surface and pump (or downhole). Surface dynocards have been in use for over 80 years. They represent plots of measured rod loads at the various stroke positions, where the load is typically measured in pounds of force and the position (or rod displacement) is measured in inches. An example of a surface dynocard is shown in Figure 2.

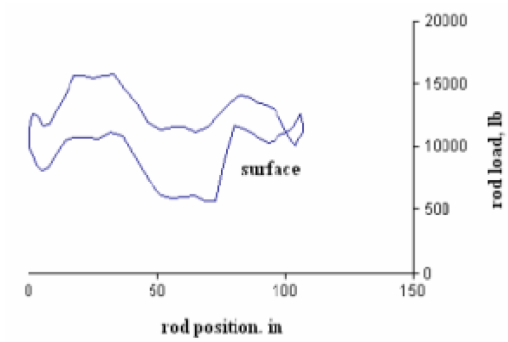



Figure 2—Surface dynocard example; source: S. G. Gibbs

The shape of the surface dynocard is affected by changing downhole conditions. Traditionally, these conditions are determined from the card by visual interpretation of an experienced analyst. This method has been proven ineffective in multiple conditions; hence, a better assessment of what truly reflects downhole conditions was needed. That's the reason the downhole dynocard was invented. The only way to truly measure downhole dynocards is to pull the sucker rods and the pump itself out of the well, which is cost prohibitive given large deployments. A method introduced by S. G. Gibbs used differential equations to calculate the card values. Therefore, the downhole dynocard can be defined as a plot of the calculated loads at various rod displacement positions of the pump stroke; the downhole card represents the load that the pump applies to the bottom of the rod string. The downhole dynocard load is generally negative. Using S. G. Gibbs' equations, an example of a downhole dynocard corresponding to the surface dynocard is shown in Figure 3.

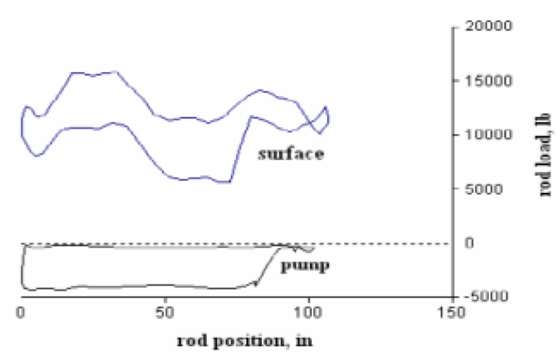
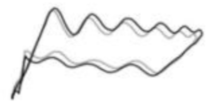
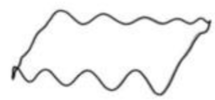
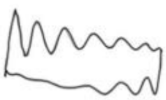
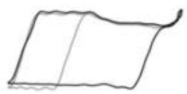
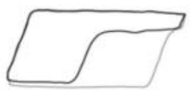
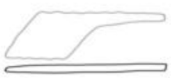
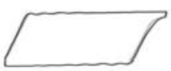
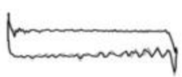



Figure 3—Downhole dynocard example; source: S. G. Gibbs

Identification and diagnosis of beam pumps using the valuable dynocard is an expensive human visual interpretation process. It does not only require significant labor time but also requires deep expertise in this technical domain. Wrongly calculated dynocards lead to incorrect control/optimisation of the well and consequently hidden deferment. A summary of these dynocards and their equivalent description is shown in Table 1.

**Table 1—Typical Beam Pump wells Dynocards.[3]**

| Shape | Description | Shape | Description | Shape | Description |
|---|---|---|---|---|---|
|  | Insufficient liquid supply |  | Severe insufficient liquid supply |  | Insufficient liquid supply and vibration |
|  | Insufficient liquid supply and friction |  | Collide pump |  | Collide pump and vibration |
|  | Gas influence |  | Gas influence and vibration |  | Vibration |
|  | Severe vibration |  | Suspected carrier bar failure |  | Full load production |
|  | Sudden slight fluctuations of liquid supply |  | Sudden large fluctuations of liquid supply |  | Sudden severe decline of liquid supply |
|  | Sudden general gas interference |  | Sudden severe gas interference, air lock |  | Sudden traveling valve cannot open |
|  | Sudden traveling valve leakage |  | Sudden standing valve cannot open |  | Sudden standing valve leakage |
|  | Plunger pull-out from work barrel |  | Sudden tubing leakage |  | Sudden increase of friction |
|  | Sudden sucker rod break |  | Foreign matter in the pump |  | Severe gas interference |
|  | High performance production |  | Natural flowing |  | Pump leakage |

Currently, oil and gas operators and owners are faced with the challenge of safely and efficiently managing their ageing plant and assets. This challenge is compounded by poor historic records and information, and the potential loss of knowledge as the current workforce retires. Coupled with the increasing requirement for high levels of design assurance and confidence in solutions, and the constant pressure to deliver value, faster and cheaper; companies are constantly looking at the latest technological advances, and to other industry sectors, for possible solutions. Specifically, in those South Oman fields was difficult to make a comprehensive analysis for operation of the bean pumping wells with multiple faults of load cells, down-hole conditions due to the increased wells population (+2000).

Machine intelligence allows equipment to sense conditions in their local environment, recognize and solve basic problems and operate independently of human direction. The main objective of this document is to describe Sucker Rod Pump or Beam pumps wells maintenance improvements and hidden production detection applying Machine Learning (ML).

## How agile can be the basis for the solution?

In recent years, the concept of "agile" has been front and center in the software application world as a means to drastically improve development velocity, scalability, and overall performance. The same guiding principles can be applied to asset heavy industries, helping teams manage field development, well delivery, and other operational challenges in oil and gas. Agile was originally developed for the software industry to streamline and improve the development process in an effort to rapidly identify and adjust for issues and defects. It provides a way for developers and teams to deliver a better product, in a faster manner, through short, iterative, interactive sessions/sprints. In the era of digital transformation, with many companies migrating to a digital workplace, agile is a perfect fit for organizations looking to transform how they manage projects and operations and operate it as a whole. Agile can help ensure company-wide process and methodological alignment.

How can shale operators—and other organizations in asset-heavy industries—use this new asset development approach to improve capital efficiency and well performance? In a traditional assembly-line manufacturing approach, emphasis is placed on well construction efficiency and lean principles to enable speed and scale. By applying agile, the focus on efficiency can be balanced with experimentation and accelerated learning to rapidly identify improvement opportunities. The shift to agile project management in oil and gas could deliver a structured, iterative, and repeatable process. It could also afford time to reflect and adjust field development and well delivery strategies based on near-real-time results of targeted experimentation and rigorous well performance assessments.

Many leaders in asset-heavy companies first hear about agility through their internal digital transformations. Digital and agility go hand in hand, and digital efforts that don't embrace agile delivery models will struggle to sustain themselves and scale up later. Companies often establish special units—digital factories, garages, accelerators, incubators, studios, labs—to execute at speed. In some companies, these are part of the mainland; in others they are islands. Invariably, they include cross-functional business and IT teams (often called squads), using some variant of the scrum methodology to deliver their work. In almost all examples, the speed of delivery and usability of solutions improve dramatically.[4] An incremental, iterative approach forms the basis for Agile methodology. The Agile philosophy encourages constant feedback from the end-user and working with changing requirements is one of its core tenets. Cross-functional teams work on versions of a product over time. A Backlog prioritizes relevant tasks and ensures these are at the front of the task list. Business or customer value primarily dictates this priority. A time-boxed sprint defines the number of work items that will get done in each Sprint. At the end of each sprint a working version of the product is ready for user feedback.

End to end, cross-functional squads are the most widespread agile archetype, applicable wherever teams solve problems together to deliver products, projects, or other activities requiring creativity. These teams should have the knowledge and skills to deliver desired outcomes and, as far as possible, a mission representing the end-to-end delivery of the associated value stream. We have seen this model applied successfully to activities as diverse as front-end capital projects, the improvement of operational performance (such as throughput, sand management, and energy efficiency), asset planning, and M&A.

## Scope

In this case an application (AFKAR) was developed to analyse the measurement data from the beam pump and detect abnormal conditions that cause improper operation of the pump and lead to deferment and potentially to mechanical damage.

For the operations team to shift from a lagging to a proactive beam pump wells surveillance through leading indicators, it is necessary to observe and analyze 24×7 each dynocard (load and position values during a stroke). This is very time consuming and error prone work since electrical failures (e.g. damage load cell cable) can be mistaken for a mechanical failure. The challenge is that there are insufficient Field Programmers surveying minute by minute over 3300+ wells, including 1100+ beam pump wells. It is not possible to manually check the dynocard of every well. AFKAR will identify the wells that do need to be looked at.

AFKAR automatically analyses the dynocards collected every day and classifies each as *Normal* or *Abnormal*. For the trial the beam pump wells of those fields were selected which gave a well count of more than 100, sufficient to provide a representative sample of the faults AFKAR was designed to identify.

For the trial a web interface was developed for viewing the results of the analysis by AFKAR. This provided:

- A count of the total dynocards analysed that day, how many were classified as *Normal* and how many were classified as *Abnormal*.
- All the dynocards collected that day were available to view.
- The user could select to view only the *Abnormal* cards for the day.
- The user could select an individual well and view all the dynocards for that well for the entire period of the trial.
- A Visual Management dashboard was included to show how all the wells were performing for a specified number of days thus allowing recurring problems to be identified.

It is important to note that machine learning algorithms are not a substitute for expert operators and engineers. While these models can accurately diagnose problems, the final root cause analysis and well operation requires extensive experience and problem solving to effectively determine the proper course of action. These models do not replace the well review.

## Technical Working Group

A multi-discipline Technical Working Group was created to use and evaluate the AFKAR application during the trial. This group included experienced Field Programmers who would use the tool alongside their existing surveillance systems, Beam Pump Subject Matter Experts and the analytics and engineering team that developed and deployed the AFKAR application.

During the period of the trial, for 3 months from April to July, it was the Working Group who were using the AFKAR application on a day-to-day basis. Weekly meetings were held to discuss findings, to dig into details on individual wells and to suggest potential improvements. Towards the end of the trial period the Working Group performed a Blind Test to objectively assess how well AFKAR performed its main function of classifying dynocards as Normal or Abnormal.

## Data Preparation & Blind Test Methodology

AKFAR classifies dynocards as *Normal* and *Abnormal*. These dynocards are collected by schedule and as they become available, they are classified accordingly. Its user interface summarizes the last 24 hours predicted detection with the total analyzed dynocards, the number of dynocards classified as *Normal* and the number of dynocards classified as *Abnormal*. The dynocards classified as *Abnormal* are highlighted with a light red background, while those classified as *Normal* are marked with a white background.

For the Blind Test, the previous 24 hours dynocards were used at the time of the blind testing. Right before the test, the classification color coding was removed, and each card was be evaluated by Subject Matter Experts as *Abnormal* or *Normal* (the ground truth). Once the ground truth cases were registered, the AFKAR user interface was refreshed and the classified dynocards as *Abnormal* or *Normal* were recorded as True/False and Positive/Negative in a confusion matrix.

The AFKAR data-driven models were trained to detect abnormal dynocards. Therefore, the positive class means the model successfully detected the failure and the negative class means the model wrongly detected the failure.

*A true positive (TP)* is an outcome where the model correctly predicts the positive class. Similarly, *a true negative (TN)* is an outcome where the model correctly predicts the negative class.

*A false positive (FP)* is an outcome where the model incorrectly predicts the positive class. In addition, *a false negative (FN)* is an outcome where the model incorrectly predicts the negative class.

**In other words, true positives are defined as captured failures, false negatives as missed cases, false positives are the false alarms and the true negatives as the cases in which no failure were captured for non-failure data.**

## Metrics

A confusion matrix is a popular representation of the performance of classification models. The reason that the confusion matrix is particularly useful is that, unlike other types of classification metrics such as simple accuracy, the confusion matrix generates a more complete picture of how a model performed.

The matrix (table) shows us the number of correctly and incorrectly classified examples, compared with the actual outcomes (target value) in the test data. One of the advantages of using the confusion matrix as evaluation tool is that it allows more detailed analysis (such as if the model is confusing two classes), than simple proportion of correctly classified examples (accuracy) which can give misleading results if the dataset is unbalanced (i.e., when there are huge differences in the number of between difference classes).

The matrix is *n* by *n*, where *n* is the number of classes. The simplest classifiers, called binary classifiers, have only two classes. Performance of a binary classifier is summarized in a confusion matrix that cross-tabulates predicted and observed examples into four options:

The list of metrics to be calculated as part of this Blind Test as follows:

1. Sensitivity
2. Specificity
3. Precision
4. Negative Predictive Value
5. False Positive Rate
6. False Discovery Rate
7. False Negative Rate
8. Accuracy
9. F1 Score
10. Matthews Correlation Coefficient

*Precision* explains how many correctly predicted values came out to be positive actually. Or simply it gives the number of correct outputs given by the model out of all the correctly predicted positive values by the model.

Finally, *Accuracy* explains how regularly the model predicts the correct outputs and can be measured as the ratio of the number of correct predictions made by the classifier over the total number of predictions made by the classifiers.

Terms of reference are explained below:

| **Analytics Terminology** | **Real world meaning** |
|---|---|
| **True Positive (TP)**<br>The predicted value matches the actual value.<br>The actual value was positive and the model predicted a positive value | AFKAR correctly predicts an abnormal dynocard |
| **True Negative (TN)**<br>The predicted value matches the actual value<br>The actual value was negative and the model predicted a negative value | AFKAR correctly predicts a normal dynocard |
| **False Positive (FP)** – Type 1 error<br>The predicted value was falsely predicted<br>The actual value was negative but the model predicted a positive value. | AFKAR wrongly predicts an abnormal dynocard |

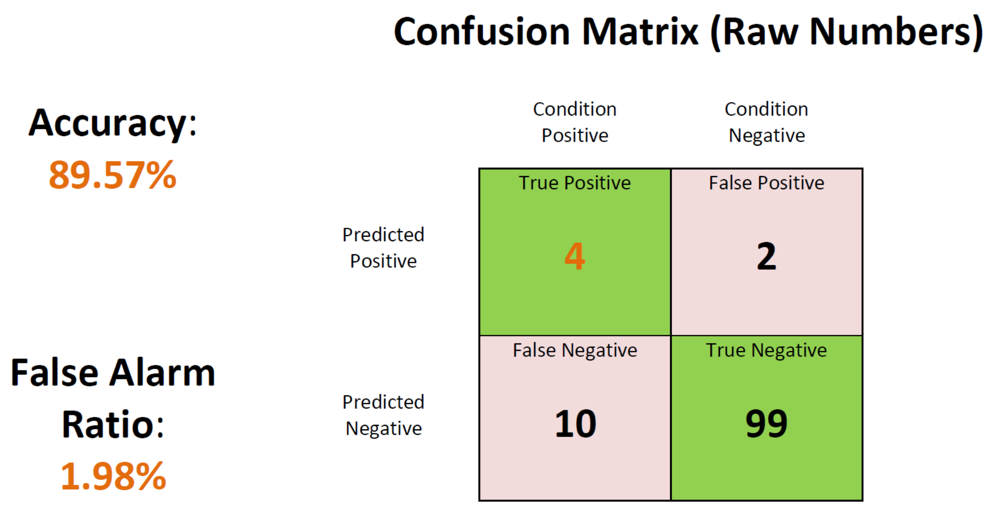
| Analytics Terminology | Real world meaning |
|---|---|
| **False Negative (FN)** – Type 2 error<br>The predicted value was falsely predicted.<br>The actual value was positive but the model predicted a negative value. | AFKAR wrongly predicts a normal dynocard |

## Results

During the work session held for the Blind Test, a total of 460 evaluations were carried out from 115 failure cases from 115 wells. For each well and failure case, the team first evaluated the possible abnormal cases (by eye) as flagged as the ground truth. For each well, the team analysis and comments were captured.

These evaluations were distributed into four classes: True Positives (captured failures); False Positives (false alarms), True Negative (no failure captured during normal / non-failure operation) and False Negatives (missed failures). Each case was captured in a digital dashboard.

## Confusion Matrix




## Summary of findings

- Altogether, the Well Failure data-driven model made 115 scores/dynocards for 115 wells. 115 cases were classified as Failure or Non-Failure class.
- Out of 115 cases, the model correctly classified 104 cases: 99 were correctly classified as non-Failure, and 4 of them were correctly classified as Failure. This result to 89.57% accuracy.
- The model showed an outstanding fall-out or false alarm ratio with a 1.98% false positive ratio.
- Furthermore, 12 out of 115 cases were classified falsely: 10 cases, which were actual Failures, were missed and not predicted as Failure (False Negative). In addition, more important, only 2 cases of non-Failure were falsely predicted as Failure (False Positive), which is very desired in this case (minimum false alarms).
- We can observe that the model is very conservative when it comes to predicting Failures, with a precision of 66.67%.
- All cases which will affect the pump fillage calculation and therefore runtime were captured.
- Model managed to capture all failure cases which were trained to. However, several of the missed cases could be added into AFKAR as continuous improvement.

## Metrics

By computing additional measures from the classification matrix, we can get additional insight about the model as follows:

| Measure | Value | Derivations |
|---|---|---|
| Sensitivity | 28.57% | TPR = TP / (TP + FN) |
| Specificity | 98.02% | SPC = TN / (FP + TN) |
| Precision | 66.67% | PPV = TP / (TP + FP) |
| Negative Predictive Value | 90.83% | NPV = TN / (TN + FN) |
| False Positive Rate | 1.98% | FPR = FP / (FP + TN) |
| False Discovery Rate | 33.33% | FDR = FP / (FP + TP) |
| False Negative Rate | 71.43% | FNR = FN / (FN + TP) |
| Accuracy | 89.57% | ACC = (TP + TN) / (P + N) |
| F1 Score | 40.00% | F1 = 2TP / (2TP + FP + FN) |
| Matthews Correlation Coefficient | 39.10% | TP*TN - FP*FN / sqrt((TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)) |

## Lessons Learned & Results of the Trial

On completion of the 3-month trial period, a manual analysis of the data from every well included in the trial scope was conducted. This analysis looked at the operation of the well and whether there was any period of deferment not booked in the Hydrocarbon Accounting System, where no other existing system raised a notification and where AFKAR identified an abnormal dynocard. In the 3-month period that AFKAR was operational it identified substantial hidden deferment, wells that were not identified by any existing surveillance system as incurring periods of deferment. Detecting this hidden deferment clearly provides scope for improved production and also for improving the field Reconciliation Factor. Given the rapid and low-cost development of the AFKAR, a conservative estimate of the potential value of AFKAR implemented for all operating beam pumps would yield a VIR (Value Investment Ratio) of more than 30.

The results of the Blind Test clearly demonstrate that AFKAR can reliably classify dynocards as Normal or Abnormal and the individual well analysis highlights the potential value in terms of hidden deferment.

In addition, the users and Subject Matter Experts identified many further enhancements such as: other dynocard shapes that would be useful to detect, more frequent dynocard collection, linkage to run time data and well test data.

In summary, the AFKAR Proof of Concept was highly successful in demonstrating the rapid speed of an Agile development and the real business value that analytics can bring to an organization.

## Conclusions

Machine Learning (ML) can help companies make the switch to predictive maintenance by modelling sensor data to find problematic equipment. If there are anomalies in the dataset, such as equipment operating outside its parameters, then the equipment can be maintained before it is damaged. Damaged equipment leads to safety issues and reduced production.

It is difficult to make a comprehensive analysis for operation of the bean pumping wells with multiple faults of load cells, down-hole conditions, which cannot be effectively dealt with by the traditional methods. Having the right agile methodology and the right team was an essential factor to successfully accomplished this work in less than four months.

Predictive maintenance can also reduce environmental impact. Well-maintained equipment fails less, so fewer spills happen. Spills in the industry can be almost impossible to completely clean up and can have far-reaching effects on people, water, animals, and soil.

## Recommendations

As general observations (voice of internal customers):

1. AFKAR proved to be able to identify cases where a deep dive can be done.
2. Data-driven failure alarms should trigger Exception Based Surveillance alarms and Standard Operating Procedures need to be created. These models should work for new and inexperienced Production Technologists, Production Programmers, Operators.
3. A minority of cases were not captured by AFKAR. However, these cases could be included as part of further development e.g., elliptical and balloon shaped dynocards, cards that indicate a delay in the closure of the travelling valve, system friction, etc.
4. AFKAR should collect and analyze dynocards more frequently and on demand when requested by a user.
5. AFKAR should include a link to the well run-time to quickly identify and prioritize cases that have had an impact on production.

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